# Temporal Physical Activity Patterns are Associated with Obesity in U.S. Adults

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**Research**

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# Abstract

**Background:** Few attempts have been made to incorporate multiple aspects of physical activity (PA), including timing and volume, to classify patterns that link to health. Temporal PA patterns integrating time and activity counts were created to determine their association with health.

**Methods:** PA accelerometry data obtained from the cross-sectional National Health and Nutrition Examination Survey 2003-2006 was used to pattern PA counts and time of activity from 1,999 non-pregnant adults with one random valid weekday of activity. Constrained dynamic time warping with Sakoe-Chiba band and kernel k-means clustering grouped participants to 4 clusters representing temporal PA patterns. Multivariate regression models controlling for potential confounders and adjusting for multiple comparisons ($p$<0.05/6) determined associations between clusters and health status indicators and conditions obesity, type 2 diabetes, and metabolic syndrome.

**Results:** Participants in Cluster 2, represented by a temporal PA pattern with activity counts reaching >1.2e$^5$ counts/ h (cph) and tapering off through the day, had lower mean body mass index (BMI) ($p$<0.001), waist circumference (WC) ($p$<0.01), and 65% lower odds of obesity relative to normal weight status compared with participants in Cluster 1 with the lowest PA counts reaching 4.8e$^4$ cph from 6:00 to 23:00 (OR: 0.3; 95% CI: 0.2, 0.8). Cluster 3, characterized by a temporal PA pattern with activity counts reaching 9.6e$^4$-1.2e$^5$ cph between 16:00 to 21:00, was associated with lower mean BMI ($p$<0.001) and WC ($p$<0.01), and 60% lower odds of obesity relative to normal weight status compared to Cluster 1 (OR: 0.4; 95% CI: 0.2, 0.8). Cluster 4 characterized by activity counts reaching 9.6e$^4$ cph between 8:00 to 11:00 was associated with lower BMI and WC compared to Cluster 1 (both $p$<0.05).

**Conclusions:** U.S. adults with temporal PA patterns of higher activity counts ranging between 9.6e$^4$->1.2e$^5$ cph performed early (8:00 to 11:00), late (16:00 to 21:00), or throughout the day had significantly lower mean BMI and WC compared with adults with a temporal PA pattern of the lowest PA counts reaching 4.8e$^4$ cph from 6:00 to 23:00. Temporal PA patterns created by integrating time with PA counts throughout a day meaningfully link to health status.

# Introduction

Obesity is a global health problem with about 13% of the world's adult population considered obese in 2016 [1]. Prevalence estimates of obesity in the United States (U.S.) increased between 2003–2004 and 2013–2014, reaching 42.4% among adults in 2017–2018 [2]. Obesity is both an outcome and a contributor to chronic disease development including type 2 diabetes and metabolic syndrome [3,4]. Low physical activity (PA) behavior is a potentially modifiable risk factor for obesity [5]. Though trends in meeting the U.S. PA Guidelines have improved between 2008–2018 based on self-reports [5,6], percentages of U.S. adults meeting both aerobic and muscle strengthening guidelines remain low at around 20.6% [7].

Engaging more of the population in PA is a public health priority given its well documented beneficial effects. Specifically, increased exercise has been shown to aid in weight loss and maintenance [8], lower waist circumference (WC) [9], blood pressure [10], and postprandial triglycerides [11]. Moreover, most previous PA research has focused on the association between intensity (i.e., moderate to vigorous) or counts of PA and health outcomes [11–14]. Beyond these two aspects of activity, the timing of activity may also be relevant to health. A few studies have showed a potential benefit to modulating time of activity in relationship with health outcomes [15–18]. For instance, one study reported higher odds of obesity in women who were less active in the morning hours compared to the evening [15], while another randomized clinical trial revealed significant lowering of body mass index (BMI) after 6 weeks of aerobic exercise was performed in the morning vs. evening in a group of women with overweight [16]. A limitation of these studies is a focus on vague unspecified parts of the day i.e., morning vs. evening without considering the specific timing of these activities or activity counts at other time points during the day. Consideration of the pattern of activity throughout a day, or “temporal PA patterns”, may provide insight to the behavioral patterns related to health, however studies on temporal PA patterns are scarce. One of the challenges in this work is utilizing methods that will characterize PA patterns as an exposure by integrating timing and other characteristics of PA in relation to health.

A novel distance measure based on dynamic time warping (DTW) is used herein to identify similarities in the time and counts of activity over a 24-hour period and to perform dimensionality reduction. Groups exhibiting similar activity throughout the day are expected to display similar health status indicator values and risk of chronic disease that are distinct from other temporally defined groups. Thus, the hypothesis for this study is that differences in health status exist between U.S. adult (aged 20–65 y) participant clusters demonstrating similar 24-hour temporal PA patterns as generated from accelerometry data of the 2003–2006 National Health and Nutrition Examination Survey (NHANES).

## Methods

## Participants and Data Collection

NHANES is a program of studies designed to assess the health and nutritional status of adults and children in the U.S. [19]. Participants were recruited using a complex, stratified, multistage probability sampling design in order to represent the civilian non-institutionalized U.S. population [19]. Participant characteristics including age, sex, race/ethnicity, and income to poverty ratio (PIR) were collected using an in-depth questionnaire during the in-person household interview. Survey participants were interviewed in their homes and subsequently examined in the mobile examination center. The health examination included the collection of anthropometric measurements, laboratory tests, and recruitment for the PA assessment component. Consent was obtained from all participants and NHANES protocols and content were approved by the National Center for Health Statistics (NCHS) Research Ethics Review Board [20].

## Analytic Sample

The NHANES data are released in 2-year cycles; because PA accelerometry data was collected and publicly released for survey years 2003–2004 and 2005–2006, these 4 years of data were combined for this analysis. Previous studies show no significant differences in the PA levels in these two survey cycles [21]. Data used for this analysis included non-pregnant U.S. adults aged 20–65 y with one random weekday of valid accelerometer data and complete sociodemographic, anthropometric and laboratory data (n = 1,999) (Additional File 1). Pregnant women, children, adolescents, and adults older than retirement age were excluded because their daily activity patterns may include variation characteristic to the life stages they represent [5].

# Anthropometric Assessment and Laboratory Tests

Selected health status indicators were chosen for their previous associations with PA [10,11,22,23]. Details of NHANES methods have been widely reported but are summarized briefly here. Weight was measured using a digital scale to the nearest 0.1 kilogram [24]. Standing height and WC were measured with a stadiometer and tape measure, respectively to the nearest 0.1 centimeter [24]. BMI was calculated as weight in kilograms divided by height in meters squared [25].

A phlebotomist obtained blood samples from participants according to a standardized protocol [26,27]. Fasting plasma glucose and triglycerides were assessed after participants fasted at least 8 hours and not more than 24 hours. Fasting plasma glucose was measured using a hexokinase method with a Roche/Hitachi 911 (cycle 2003–2004) or a Roche Cobas Mira (cycle 2005–2006) [28,29]. Triglycerides were measured enzymatically [30,31]. Hemoglobin A1c, total cholesterol, and high-density lipoprotein cholesterol (HDL-C) were based on samples taken regardless of fasting state. Hemoglobin A1c was measured with high performance liquid chromatography using Primus CLC 330 and Primus CLC 385 in the 2003–2004 cycle and using Tosoh A1c 2.2 Plus Glycohemoglobin Analyzer in the 2005–2006 cycle [32,33]. Total cholesterol was measured enzymatically. An instrument change occurred in NHANES 2005–2006 for total cholesterol, but the method and laboratory location were similar to 2003–2004 cycle [34,35]. HDL-C was analyzed using a direct HDL-C immunoassay method from 2003–2006 and similarly, a change in equipment to measure HDL-C was made for 2005–2006, yet the laboratory method and location were similar to 2003–2004 [34,36]. Blood pressure was measured using a mercury sphygmomanometer, with systolic and diastolic blood pressures determined based on up to 4 measures [37]; if more than 1 measure was obtained, the first measure was not considered, and the remaining measures were averaged, otherwise, the first measure was used.

# Accelerometer Data Collection and Analysis

The ActiGraph model 7164 accelerometer was used to collect objective information on participants' PA. One-min time intervals (epochs) were used to assign a count value which is a relative measure of changes in momentum that occurred during these intervals and which then could be converted to an estimate of PA intensity [38]. Monitors began recording activity information (for 7 consecutive days) at 12:01 a.m. the day after the health examination [39]. Accelerometer data were analyzed using SAS programs developed by the National Cancer Institute [40]. Ten hours of wear time was considered a valid day which was calculated by subtracting non-wear time (i.e., periods of ≥ 60 consecutive min of zero activity counts allowing for intervals of 1–2 consecutive min of relatively low activity counts i.e., 1-100 counts) from the total daily observation time (24 hours) [41]. Given the exploratory nature of this analysis, one random weekday of valid accelerometer data was chosen at this first attempt to develop temporal PA patterns using a data-driven technique based on DTW. From each person's valid days, one day was randomly selected so that each valid day had an equal chance of being chosen. Inclusion of all activity types e.g., light intensity, has the advantage of holistically evaluating PA links to health throughout the day and align with the goals of the study. Total activity counts (TAC)/day, a proxy for total volume of PA performed, accounts for minutes spent in sedentary, light, moderate, and vigorous activity and weights each minute according to intensity [42]. TAC/day also has the advantage of integrating several PA components including intensity, duration, and frequency and combining them into an overall measure of PA [43] and have been found to be more closely linked to cardiometabolic biomarkers compared to minutes of moderate-to-vigorous PA (MVPA) accumulated in ≥ 10-min bouts [44]. Therefore, TAC/day was used in the current study, in which activity counts collected at every minute over one day was used to investigate how PA is distributed in time.

# Temporal Physical Activity Patterns

Several distance measures for comparing time series were investigated including the constrained DTW with Sakoe-Chiba band (CDTW) and the modified DTW (MDTW) based on previous work to pattern dietary intake [45]. The original and the compact representation of PA time series are the required input format by CDTW and MDTW, respectively. PA counts collected on one random weekday of activity were used to develop the original time series of length 1440, with each entry representing counts per minute. The same data was used to form the compact representation by summing PA counts in each hour and extracting the counts and hourly time stamps of non-zero hours similarly as defined in previous studies [46,47]. Both CDTW and MDTW belong to the elastic distance family and find the optimal matching path among counts of activity in two time series [45]. The matching is "optimal" in the sense that the summed difference between matched counts is minimized. The Sakoe-Chiba bandwidth in CDTW and the weight parameter beta in MDTW are controlling parameters to avoid pathological matchings (e.g., matching morning to evening activities). While the Sakoe-Chiba band rigorously limits the maximum time difference between matched entries, the weight parameter beta controls the matching through a time difference penalty term: larger beta indicates more penalty on matching entries that are different in time. Bandwidths ranging between 60–720 min (60-min increments) and beta ranging from 0–10 (1 increment) were explored in CDTW and MDTW, respectively and parameter values outside of these ranges were omitted as they did not bring significant changes in the clustering results. Further, the distance measures were coupled with kernel k-means algorithm [48] to partition the time series into several clusters such that activity occasions are more similar in the same cluster and more dissimilar among different clusters. Cluster number k = 4 was selected to divide the population into clusters representing similar temporal PA patterns to maintain consistency with previous development of temporal patterning [45,47,49]. CDTW with bandwidth 240 min (i.e., representing a constraint of a maximum of 4 hours between two matched activity occasions) performed the best compared with CDTW over the values of bandwidth, and also compared with MDTW over the values of beta based on inferential analyses with health status indicators prioritized as: 1) most significant differences between the six pairwise comparisons, 2) highest model $R^2$ values, and 3) largest difference between highest and lowest mean of health status indicators. The analysis of the clusters for CDTW with bandwidth 240 min is presented in the sequel.

# Statistical Analysis

The Rao Scott F adjusted chi-square statistic was used to determine significant differences among clusters by selected characteristics: survey year (2003–2004 and 2005–2006), sex (male or female), race/ethnicity (Mexican American and other Hispanic, Non-Hispanic white, Non-Hispanic black, and other-race including multi-race), age groups (20–34, 35–49, and 50–65 y), PIR, and BMI categorized as underweight (< 18.5 kg/$m^2$), normal weight (18.5–24.9 kg/$m^2$), overweight (25.0-29.9 kg/$m^2$), and obese (≥ 30.0 kg/$m^2$) [25]. PIR, calculated as reported household income divided by the federal poverty guideline for household income, was divided into six categories: 0-0.99, 1-1.99, 2-2.99, 3-3.99, 4-4.99, and ≥ 5. Ratios < 1 indicate a PIR below the officially defined poverty level [50].

Disease categories included obesity, diabetes, and metabolic syndrome. Diabetes classification was based on fasting plasma glucose (≥ 126 mg/dL), hemoglobin A1c (≥ 6.5%) or self-report of: “yes” in response to the question “have you ever been told by a doctor you have diabetes?” or to the use of glucose-lowering medications [51]. The National Cholesterol Education Program Adult Treatment Panel III definition of metabolic syndrome was applied to classify this condition based on the presence of three or more of the following risk factors: 1) WC (>102 cm for men, >88 cm for women); 2) triglycerides (>150 mg/dL) or taking antihyperlipidemic medications; 3) HDL-C (<40 mg/dL in men, <50 mg/dL in women); 4) hypertension (>130/>85 mmHg) or taking antihypertensive medications; and 5) impaired fasting glucose (>110 mg/dL) or taking glucose-lowering medications [52].

Analysis of variance determined differences in means of health status indicators by temporal PA patterns. Multiple linear regression models determined associations between four temporal PA patterns and health status indicators. For risk of obesity, type 2 diabetes, and metabolic syndrome, multivariate logistic regression was used to estimate odds ratio comparing the four temporal PA patterns. For both linear and logistic models, potential confounders included survey year, sex, age group, race/ethnicity, PIR, TAC and BMI (except for models with BMI, WC, and obesity as the outcome). Appropriate survey weights were constructed for the 2003–2006 survey years as directed by the NCHS [53]. Sampling weights were rescaled so that the sum of the weights matched the survey population at the midpoint of the 4 years covering 2003–2006. Adjustment for the complex survey design including clustering and stratification was completed following NCHS guidelines [44]. Comparisons between groups were considered statistically significant when $p < 0.05/6$ (Tukey-Kramer type adjustment for multiple comparisons). Analyses were completed using SAS survey procedures and inferential analysis version 9.4.

# Visualization

The visualization (Fig. 1) illustrates the distribution of non-zero PA counts in each cluster using heat maps. Each activity occasion in the heat map is marked by its time stamp (x-axis) and PA counts (y-axis). Time axis ranged from 0 = 12:00 to 24:00 the next day with PA counts (y-axis) ranging from 0 to > $1.2e^5$ counts at a particular hour. The proportion of individuals that had the corresponding activity (certain activity count and time stamp) is indicated through shading and ranged from 0–12.6% of each cluster. Darker shading signifies that a greater proportion of that cluster engaged in the specified PA counts at that specific hour. Figure 1 exhibits four distinct temporal PA patterns of activity occasions. Figure 2 adds color in order to differentiate the 4 clusters.

**Figure 1** Heat maps for CDTW clusters (A-D) which depict activity counts ranging from 0 counts/hour (cph) to > $1.2e^5$ cph (y-axis) for U.S. adults ages 20–65 y as drawn from NHANES 2003–2006 over a 24-hour day from time 0 = 12:00 to 24:00 the next day (x-axis). The proportion of the sample is indicated by the inverse gray-scale legend with 0.0% of the cluster participants to 12.6% of the cluster participants.

**Figure 2** Heat maps for CDTW clusters (C1-C4) which depict the distribution of the largest activity occasion within each cluster for U.S. adults ages 20–65 y as drawn from NHANES 2003–2006. The activity counts ranged from 0 cph to > $1.2e^5$ cph (y-axis) over a 24-hour day from time 0 = 12:00 to 24:00 the next day (x-axis). The proportion of the sample is indicated by the inverse color-scale legend with 0.0% of the cluster participants to 6.1% of the cluster participants.

# Results

Characteristics of participants in the four clusters representing temporal PA patterns are presented in Table 1. Clusters 2 and 3 included proportionately equivalent numbers of participants, 12.4% and 16.8%, respectively, whereas Cluster 1 had the largest proportion (39.2%) followed by Cluster 4 (31.6%). Significant differences were present among clusters by sex ($p$ < 0.0001), age ($P$ < 0.0001), PIR ($p$ < 0.02), and BMI ($p$ < 0.0001), but not by survey year or race/ethnicity. Females were more heavily represented in Cluster 1 (64.1%), while males featured more prominently in Cluster 2 (78.9%). Additionally, Cluster 1 included a higher proportion of age group 50–65 y compared to other age groups (47.8%), whereas Clusters 2 and 3, included a higher proportion of the age group 20–34 y (44.9% and 45.5%, respectively). Further, smaller proportions of individuals at the lowest household PIR (0 to 0.99) were included in Cluster 2 (14.6%), Cluster 3 (14.9%) and Cluster 4 (14.5%), whereas larger proportions were included in Cluster 1 (18.6%). The proportional representation of Clusters 2, 3, and 4 in the higher ratios of household PIR of ≥ 5.00 compared with Cluster 1 was also observed. Regarding BMI, normal weight was more highly represented in Clusters 2 and 3 (42.5% and 37.8%, respectively) compared to Clusters 1 and 4 (22.5% and 26.4%, respectively); while obese category was more heavily represented in Clusters 1 and 4 (45.8% and 33.8%, respectively) compared to Clusters 2 and 3 (21.1% and 27.1%, respectively).

Table 1
Characteristics of clusters representing temporal PA patterns of U.S. adults ages 20–65 y NHANES 2003–2006 ($n$ = 1,999).

| **Characteristic** | **Total (*n*)** | **Cluster 1** | **Cluster 2** | **Cluster 3** | **Cluster 4** | ***p*-value[a]** |
|---|---|---|---|---|---|---|
| *n (%)* | | | | | | |
| Total | 1999 | 783 (39.2) | 247 (12.4) | 336 (16.8) | 633 (31.6) | |
| Survey year | | 0.38 | | | | |
| 2003–2004 | 975 | 384 (49.0) | 120 (48.6) | 178 (53.0) | 293 (46.3) | |
| 2005–2006 | 1024 | 399 (51.0) | 127 (51.4) | 158 (37.0) | 340 (53.7) | |
| Sex | | <0.0001 | | | | |
| Male | 1029 | 281 (35.9) | 195 (78.9) | 185 (55.1) | 368 (58.1) | |
| Female | 970 | 502 (64.1) | 52 (21.1) | 151 (44.9) | 265 (41.9) | |
| Race/Ethnicity | | 0.11 | | | | |
| Mexican American | 428 | 143 (18.3) | 53 (21.5) | 61 (18.2) | 171 (27.0) | |
| Other Hispanic | 58 | 17 (2.2) | 9 (3.6) | 10 (3.0) | 22 (3.5) | |
| Non-Hispanic white | 982 | 387 (49.4) | 124 (50.2) | 178 (53.0) | 293 (46.3) | |
| Non-Hispanic black | 427 | 187 (23.8) | 54 (21.9) | 66 (19.5) | 120 (19.0) | |
| Other | 104 | 49 (6.3) | 7 (2.8) | 21 (6.3) | 27 (4.2) | |
| Age group (year) | | <0.0001 | | | | |
| 20–34 | 616 | 177 (22.6) | 111 (44.9) | 153 (45.5) | 175 (27.6) | |
| 35–49 | 691 | 232 (29.6) | 93 (37.7) | 113 (33.6) | 253 (40.0) | |
| 50–65 | 692 | 374 (47.8) | 43 (17.4) | 70 (20.9) | 205 (32.4) | |
| Household PIR | | 0.02 | | | | |
| 0-0.99 | 324 | 146 (18.6) | 36 (14.6) | 50 (14.9) | 92 (14.5) | |
| 1.00-2.99 | 459 | 181 (23.1) | 59 (23.9) | 73 (21.7) | 146 (23.1) | |
| 2.00-2.99 | 308 | 138 (17.6) | 37 (15.0) | 47 (14.0) | 86 (13.6) | |
| 3.00-3.99 | 297 | 106 (13.6) | 41 (16.5) | 39 (11.6) | 111 (17.5) | |
| 4.00-4.99 | 189 | 72 (9.2) | 18 (7.3) | 36 (10.7) | 63 (10.0) | |

| Characteristic | Total ($n$) | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | $p$-value[a] |
|---|---|---|---|---|---|---|
| ≥ 5.00 | 422 | 140 (17.9) | 56 (22.7) | 91 (27.1) | 135 (21.3) | |
| BMI[b] | | | | | | <0.0001 |
| Underweight | 26 | 14 (1.8) | 3 (1.2) | 5 (1.5) | 4 (0.6) | |
| Normal weight | 575 | 176 (22.5) | 105 (42.5) | 127 (37.8) | 167 (26.4) | |
| Overweight | 682 | 234 (29.9) | 87 (35.2) | 113 (33.6) | 248 (39.2) | |
| Obese | 716 | 359 (45.8) | 52 (21.1) | 91 (27.1) | 214 (33.8) | |

*Abbreviations*: *BMI* body mass index, *PIR* poverty to income ratio.

[a]Rao Scott F adjusted $\chi^2$ $p$-value is a goodness-of-fit, one-sided test; statistical significance is indicated when $p < 0.05$. Analyses were adjusted for clustering and stratification. Sample weights were constructed and applied to the analysis as directed by NCHS. Weight were rescaled so that the sum of the weights matched the survey population at the midpoint of the 4 years covering 03–06.

[b]BMI: categories were defined per the World Health Organization [25].

# Characteristics of Temporal Physical Activity Patterns

Table 2
Qualitative description of clusters representing temporal PA patterns of U.S. adults ages 20–65 y NHANES 2003–2006 ($n$ = 1,999).

| | **Cluster 1** | **Cluster 2** | **Cluster 3** | **Cluster 4** |
|---|---|---|---|---|
| Characteristics | | | | |
| *n (%)* | 783 (39.2) | 247 (12.4) | 336 (16.8) | 633 (31.6) |
| Overall temporal pattern | Low PA counts throughout the day with a sharp decline between 19:00–21:00 | High PA counts throughout the day with a decline after 18:00 | Lower PA counts between 6:00–12:00<br>Higher counts between 16:00–21:00 | Higher PA counts between 8:00–11:00<br>Lower counts after 18:00 |
| Percentage of cluster engaging in high vs. low activity within cluster | Higher percentage ~ 6–12% engaged in low PA counts reaching up to $1.2e^4$ cph<br>Lower percentage ~ 1–3% engaged in PA counts between $2.4e^4$-$4.8e^4$ cph | Higher percentage ~ 3–8% engaged in PA counts reaching up to $7.2e^4$ cph<br>Lower percentage ~ 1–4% engaged in PA counts between $7.2e^4$->$1.2e^5$ cph | Higher percentage ~ 4–9% engaged in PA counts reaching up to $4.8e^4$ cph<br>Lower percentage 1–2% engaged in PA counts between $7.2e^4$-$1.2e^5$ cph | Higher percentage ~ 4–10% engaged in PA counts reaching up to $4.8e^4$ cph<br>Lower percentage ~ 1–4% engaged in PA counts between $4.8e^4$ – $9.6e^4$ cph |
| *Abbreviations*: *cph* counts per hour, *PA* physical activity | | | | |

Compared to all other clusters, Cluster 1 demonstrated the lowest activity counts reaching up to $4.8e^4$ cph for activity occasions throughout the day from 6:00 to 23:00 (Fig. 1 and Table 2). A more prominent decrease in activity was observed towards the end of the day between 19:00 to 21:00 with activity reaching up to $1.2e^4$ cph. Contrarily, Cluster 2 revealed a pattern with the highest activity counts reaching > $1.2e^5$ cph; the activity tended to taper off through the day with a higher percentage of the cluster performing activity reaching up to $7.2e^4$ cph after 18:00. Cluster 3 demonstrated low activity counts reaching up to $4.8e^4$ cph between 6:00 to 12:00, whereas the level of activity tended to increase towards later hours during the day reaching up to $9.6e^4$-$1.2e^5$ cph between 16:00 to 21:00 p.m. Furthermore, the activity counts in Cluster 4 were lower compared to Clusters 2 and 3 reaching around $9.6e^4$ cph between 8:00 to 11:00 and activity counts tended to be lower towards later hours of the day reaching up to $4.8e^4$ cph after 18:00. Generally, in all of the clusters, the percentage of participants engaging in high activity counts tended to be lower compared to the percentage of participants engaging in low activity counts. Figure 2 confirms patterns revealed in Fig. 1, variation in the unique patterns inherent to each cluster are apparent regarding highest and lowest activity throughout the day.

# Association of Temporal Physical Activity Patterns with Adiposity and Chronic Disease

Significant differences in mean BMI and WC were present among all clusters except for Clusters 2 and 3 in the unadjusted model ($p < 0.05$; see Supplementary Tables 1 and 2 Additional File 2). Cluster 1 had the highest observed raw mean BMI (30.3±0.3 kg/m$^2$) and WC (101.4±0.6 cm), whereas Cluster 2 had the lowest mean BMI (26.9±0.4 kg/m$^2$) and Cluster 3 had the lowest mean WC (93.9±0.8 cm) compared to the other clusters. There were significant differences in mean BMI between all clusters ($p < 0.05$) except Clusters 2 and 3 as well as 3 and 4 in the adjusted models (Table 3). There were significant differences in mean WC between all clusters ($p < 0.05$) except Clusters 2 and 3 as well as 2 and 4 in the adjusted models (Table 4). The significantly different mean BMI was greatest between Clusters 1 and 2 (β = 2.7±0.6 kg/m$^2$), similar to the results of the unadjusted model (BMI: β = 3.5±0.5 kg/m$^2$; see Supplementary Table 1 Additional File 2). The significantly different mean WC was greatest between Clusters 1 and 3 (β = 6.5±1.3 cm), similar to the results of the unadjusted model (β = 7.4±1.2 cm; see Supplementary Table 2 Additional File 2).

Table 3

Mean BMI (kg/m$^2$) and covariate-adjusted regression model results for clusters representing temporal PA patterns of U.S. adults ages 20–65 y as drawn from the NHANES, 2003-2006[a].

| Adjusted models[b] | *n (%)* | BMI[c], (kg/m$^2$) | β[d] ± SE compare to Cluster 2 | 95% CI | β[d] ± SE compare to Cluster 3 | 95% CI | β[d] ± SE Compare to Cluster 4 | 95% CI |
|---|---|---|---|---|---|---|---|---|
| Cluster 1 | 783 (39.2) | 30.3 (0.3) | 2.7 ± 0.6 | 1.1, 4.2** | 2.5 ± 0.6 | 0.9, 4.1** | 1.4 ± 0.5 | 0.1, 2.7* |
| Cluster 2 | 247 (12.4) | 26.9 (0.4) | | | -0.2 ± 0.5 | -1.4, 1.1 | -1.2 ± 0.5 | -2.5, -0.0* |
| Cluster 3 | 336 (16.8) | 27.3 (0.3) | | | | | -1.1 ± 0.5 | -2.3, 0.1 |
| Cluster 4 | 633 (31.6) | 28.6 (0.2) | | | | | | |

*Abbreviations*: *BMI* body mass index, *SE* standard error

[a]Significant differences among clusters in mean BMI were present amongst all clusters except Clusters 2 and 3 in the unadjusted model at $p < 0.05$ (see Supplementary Table 1 Additional File 2).

[b]Models were adjusted for survey year, sex, age, race/ethnicity, poverty to income ratio, and total activity counts/day.

[c]Values are Mean (SEM).

[d]ß represents difference between mean BMI of cluster and reference cluster. Differences in mean BMI are different than those between raw means because they represent differences in least square means.

Significance level: $^*p < 0.05$; $^{**}p < 0.001$

Table 4
Mean WC (cm) and covariate-adjusted regression model results for clusters representing temporal PA patterns of U.S. adults ages 20–65 y as drawn from the NHANES, 2003-2006[a].

| **Adjusted models[b]** | ***n (%)*** | **WC[c], (cm)** | **β[d] ± SE compare to Cluster 2** | **95% CI** | **β[d] ± SE compare to Cluster 3** | **95% CI** | **β[d] ± SE Compare to Cluster 4** | **95% CI** |
|---|---|---|---|---|---|---|---|---|
| Cluster 1 | 783 (39.2) | 101.4 (0.6) | 5.9 ± 1.5 | 1.7, 10.1** | 6.5 ± 1.3 | 2.9, 10.1** | 3.7 ± 1.2 | 0.4, 6.9* |
| Cluster 2 | 247 (12.4) | 94.2 (0.9) | | | 0.6 ± 1.2 | -2.8, 3.9 | -2.2 ± 1.2 | -5.4, 0.9 |
| Cluster 3 | 336 (16.8) | 93.9 (0.8) | | | | | -2.8 ± 1.0 | -5.5, -0.1* |
| Cluster 4 | 633 (31.6) | 97.6 (0.6) | | | | | | |

*Abbreviations*: *WC* waist circumference, *SE* standard error

[a]Significant differences among clusters in mean WC were present amongst all clusters except Clusters 2 and 3 in the unadjusted model at $p < 0.05$ (see Supplementary Table 2 Additional File 2).

[b]Models were adjusted for survey year, sex, age, race/ethnicity, poverty to income ratio, and total activity counts/day.

[c]Values are Mean (SEM).

[d]ß represents difference between mean WC of cluster and reference cluster. Differences in mean WC are different than those between raw means because they represent differences in least square means.

Significance level: $^{*}p < 0.05$; $^{**}p < 0.01$

Significant differences in the odds of obesity relative to normal weight status were present between all clusters except Clusters 1 and 4 as well as 2 and 3 in the unadjusted model ($p < 0.01$; see Supplementary Table 3 Additional File 2). In the adjusted models, there were significant differences between all clusters ($p < 0.05$) except Clusters 1 and 4 as well as 2 and 3 (Table 5). The significantly different odds of obesity relative to normal weight status was greatest between Clusters 1 and 2 (OR: 2.9; 95% CI: 1.3, 6.6), similar to results in the unadjusted model (OR: 3.8; 95% CI: 2.0, 7.2; see Supplementary Table 3 Additional File 2).

Table 5
Odds of obesity relative to normal weight status and covariate-adjusted regression model results for clusters representing temporal PA patterns of U.S. adults ages 20–65 y as drawn from the NHANES, 2003-2006[a].

| Adjusted models[b] | *n (%)* | OR[c,d] compare to Cluster 2 | 95% CI | OR[c,d] compare to Cluster 3 | 95% CI | OR[c,d] compare to Cluster 4 | 95% CI |
|---|---|---|---|---|---|---|---|
| Cluster 1 | 783 (39.2) | 2.9 | 1.3, 6.6** | 2.4 | 1.3, 4.3** | 1.3 | 0.7, 2.3 |
| Cluster 2 | 247 (12.4) | | | 0.8 | 0.4, 1.7 | 0.5 | 0.2, 0.8** |
| Cluster 3 | 336 (16.8) | | | | | 0.6 | 0.3, 0.9* |
| Cluster 4 | 633 (31.6) | | | | | | |

[a]Significant differences among clusters in odds ratio of obesity relative to normal weight status in the unadjusted model were similar to those in the adjusted model at $p < 0.01$ (see Supplementary Table 3 Additional File 2).

[b]Models were adjusted for survey year, sex, age, race/ethnicity, poverty to income ratio, and total activity counts/day.

[c]OR represents odds ratio of obesity relative to normal of cluster and reference cluster.

[d]Obesity was defined as BMI $\geq 30$ kg/m$^2$ [25].

Significance level: $^{*}p < 0.05$; $^{**}p < 0.01$

Regarding the other health status indicators, type 2 diabetes and metabolic syndrome, in the adjusted models, one significant difference was present in mean hemoglobin A1c, systolic blood pressure, and triglycerides between Clusters 1 and 3, 1 and 2, and 1 and 4, respectively (all $p < 0.05$) (higher mean of health status indicators in Cluster 1 compared to the other 3 clusters) (see Supplementary Tables 13–15 Additional File 3). Additionally, there was one significant difference in odds of type 2 diabetes between Clusters 2 and 4 ($p < 0.05$) (higher odds of type 2 diabetes in Cluster 2 compared to Cluster 4) (see Supplementary Table 16 Additional File 3). There were no significant differences amongst clusters in the adjusted models of all other examined health status indicators and metabolic syndrome (see Supplementary Tables 17–21 Additional File 3).

# Discussion

Temporal PA patterns generated from one valid random day of accelerometry data are associated with BMI, WC, obesity, hemoglobin A1c, systolic blood pressure, triglycerides and diabetes but not with the other health status indicators examined. Clinical relevance of differences in mean BMI and WC associated with temporal PA patterns may be contended [54–56]. Therefore, observed mean differences in health status indicators imply that temporal PA patterns may be an important health exposure that holds promise for early detection of lifestyle factors promoting health and disease in the population. Reverse causation in the observed associations cannot be ruled out using the cross-sectional study design, nevertheless, the aim of this study was not to establish causation but to investigate whether developed temporal PA patterns using a novel methodology meaningfully link to health regardless of the direction of this association.

An abundance of research examines the relationship between PA and health. Most studies have focused on categorizing participants based on intensity and frequency of activity [57–59], while others examined daily PA patterns by focusing on distinct time periods when PA was reported such as type of day (weekday vs. weekend) [60], activity phenotypes including “weekend warrior” [61,62], and seasonality [63]. A few studies investigated diurnal patterns of PA (data collected over 5–7 days) and health [64–67]. Distinct temporal PA patterns observed in this study have been detected by two other studies that used k-means and x-means clustering approaches to derive clusters using overall activity measured by metabolic equivalent of tasks (METs) and timing of PA [64,65]. Similarities with the current study include presence of an overall inactive/low activity pattern (Cluster 1) as well as two patterns of higher activity that differed in timing of activity “afternoon engaged/morning engaged” or “moderately active/evening active” in Fukuoka et al. and Neimela et al., respectively (“early/late peaks” in activity in Clusters 4 and 3, respectively).

Cluster 1 was associated with significant higher BMI, WC, and odds of obesity relative to normal weight status compared with Clusters 2 and 3, which demonstrates that a lower activity pattern (with activity counts reaching up to $4.8e^4$ cph) throughout the day is linked with the most adverse health outcomes as evidenced by prior research [57,68,69]. The fact that this cluster included the highest number of participants (39.2%) is alarming but not surprising as previous literature has documented a high level of sedentary behavior (> 50% of waking time) among U.S. adults [5,70,71]. Moreover, Cluster 1 predominantly includes ages 50–65 years, which is consistent with evidence that activity tends to decline with age [72].

Furthermore, findings of significant lower mean BMI and WC associated with Clusters 2, 3, and 4 compared with Cluster 1 with the lowest activity counts throughout the day as well as significant lower odds of obesity relative to normal weight status associated with Clusters 2 and 3 (higher activity counts throughout the day and late in a day, respectively) compared to Clusters 1 and 4 (low activity counts throughout the day or early in a day, respectively) support previous literature showing that higher activity counts are associated with improved health status [13,14,73], but add new information regarding the timing of these patterns. Additionally, the significant lower mean WC and odds of obesity relative to normal weight status in Cluster 3 (higher PA counts performed between 16:00–21:00) compared to Cluster 4 (higher PA counts performed between 8:00–11:00) is interesting as models controlled for TAC thus, these findings may indicate that observed differences could be explained by temporal differences in these patterns. Contrary to this finding, Fukuoka et al. found that a group with peak MVPA performed in the evening had significantly higher BMI and WC compared to a group with peak MVPA performed at noon [64]. Limited evidence exists regarding the relevance of time of activity through the day in terms of links to health [64–67], so further development of temporal PA patterns may allow additional exploration of time as a potentially important factor. Moreover, the integration of time and counts of activity to clustering along with the findings of clinically meaningful differences in health status, based on distinctive time and count features of activity patterns, indicates that applying a more complex patterning technique to characterize activity through the day, has the potential to unfold the complexity of behavior rather than solely describing PA patterns by sums or labels of maximum activity levels.

Certain socio-demographic characteristics such as those included in this study (Table 1) have been shown to be associated with PA-related differences in health. The temporal PA patterns with higher PA counts (Clusters 2, 3, and 4) were more heavily represented by males compared to females, which corroborates trends observed in two U.S. surveillance systems which revealed that males were significantly more likely to be physically active compared to females [74]. Additionally, the low proportion of participants with PIR level of 0-0.99 included in the clusters with higher PA counts and a respectively high proportion of participants with PIR level of 0-0.99 included in the cluster with the lowest activity counts (Cluster 1) supports findings of an inverse relationship between prevalence of PA and household poverty level [72].

In general, activity counts tended to be lower towards the end of the day (18:00 to 22:00) in all clusters except for Cluster 3. Cluster 3 is characterized by lower activity counts during earlier hours (6:00 to 12:00) with higher counts observed towards the end of the day between 16:00 to 21:00. As this cluster was more heavily represented by ages 20–34 y, perhaps these higher PA counts in the evening may reflect sports activities or going to a gym. On the other hand, Cluster 4 with higher activity counts during early hours (8:00 to 11:00) included a higher proportion of ages 35–49 y, potentially indicating PA during work.

Elements other than intensity and duration of activity such as time of activity can be an important aspect of PA patterns and may describe PA better within the context of lifestyle. Moreover, timing of activity occasions may also be tied to dietary intake and sleep-wake regimens. For instance, an individual with a “night owl” behavior pattern may have a greater evening preference and choose to exercise later in a day compared to one with an “early bird” behavior pattern with morning preference [75]. Therefore, insight into how these various factors interact within a day and as part an overall routine over longer periods of time such as a week, month, or year, may reveal stronger associations to health status compared to when they are considered separately and thus allow for more targeted interventions based on overall lifestyle, work schedules, and family life. Further, the rapid accumulation of data on health behaviors through technology-assisted assessment tools including those targeting dietary and activity patterns will provide additional data for future investigation of whether and how the timing of these activities influences health. Integrating these data will add further knowledge of how daily behavioral patterns may contribute to metabolic dysfunction and chronic disease. Moreover, utilization of complex analytic tools including data-driven methods and traditional methods of epidemiology, to integrate time to behavioral patterns including activity and dietary intake, holds promise to understand how these temporal patterns influence long-term health status.

Strengths of this research include the use of a comprehensive approach to classifying PA exposure that considers the complexity of activity over a 24-hour period rather than examining single activity occasions (i.e., in the morning or evening). In addition, the methodology used in the current study to create temporal PA patterns and compare groups by health status indicators performed similarly in terms of association with health status when compared with the traditional clustering methods based on reported activity occasion (such as by engaging in different activity levels vs. inactivity) [76,77], and the results reveal efficacy that might be enhanced by additional methodology refinement in future studies. The limitations of the study should also be mentioned. One important limitation is the small sample size representing ~ 8% of original sample of participants included in survey years 2003–2006; therefore, study results should be interpreted with caution. Of note, sample size attrition is mostly attributable to the selected age range 20–65 y and the inclusion of health status indicators examined in a fasting subsample of participants (both criteria resulted in loss of ~ 84% of the original sample). Cluster descriptions describe the group and do not represent individuals. Additionally, one valid weekday was used to represent the activity occasions of the participants; though one random valid day has been shown to be sufficient for producing reliable population-level estimates of accelerometer-measured activity [78], patterns of activity could differ based on type of day and may potentially vary more on the weekends compared with the weekdays. Thus, further studies should consider investigation of activity patterns over weekend days. Moreover, accelerometers do not capture all types of activity including static activities (e.g., riding a stationary bike or water activities such as swimming) [39]; therefore, although this is an objective measure of PA, it still may not represent the true activity levels of the U.S. population [61].

# Conclusion

Temporal PA patterns are associated with differences in BMI, WC, and obesity. Individuals with higher activity counts performed throughout the day as well as early (8:00 to 11:00) or late (16:00 to 21:00) in a day exhibited lower mean BMI and WC compared to those with lower activity counts based on objectively measured PA data collected on one random weekday. The incorporation of time of day with total counts and sequence of activity is possible to create temporal PA patterns that are related to health and could provide insight into early detection of behavioral patterns that predispose obesity and chronic disease.

# Abbreviations

BMI: body mass index; CDTW: constrained with Sakoe-Chiba band dynamic time warping; cph: counts/hour; DTW: dynamic time warping; HDL-C: high-density lipoprotein cholesterol; MDTW: modified dynamic time warping; MVPA: moderate-to-vigorous physical activity; NCHS: National Center for Health Statistics; NHANES: Nutrition and Health Examination Survey; PA: physical activity; PIR: poverty to income ratio; TAC: total activity counts/day; WC: waist circumference.

# Declarations

### Ethics approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Availability of data and materials

Not applicable.

### Competing interests

The authors declare that they have no competing interests.


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### Authors' contributions

HAE-M, ED, SG, AB, EAR, EH, MA, JG, and LL contributed to the conceptualization and methodology of the study. MA, JG, and LL analyzed the data. MA drafted the manuscript. HAE-M, ED, SG, AB, EAR, EH, MA, JG and LL critically reviewed the manuscript. All authors read and approved the final manuscript.


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# Figures

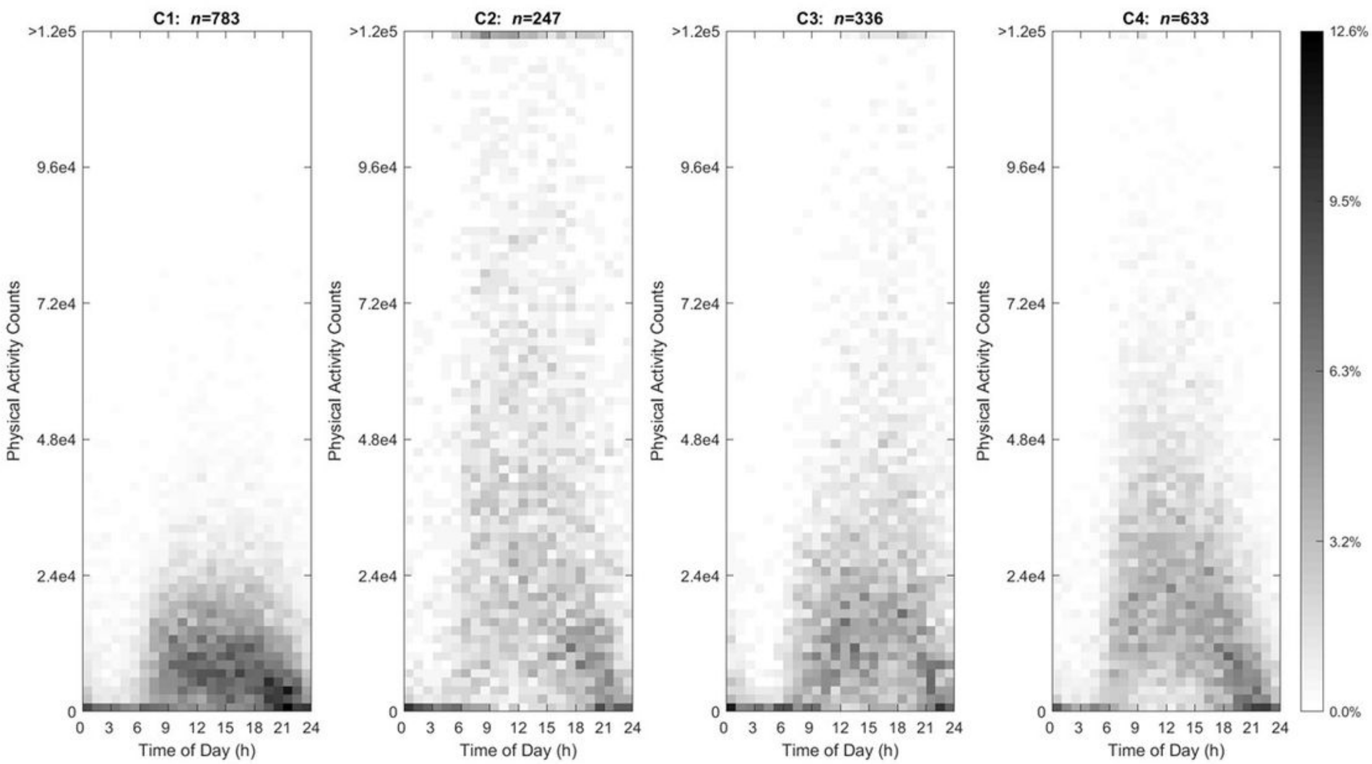


**Figure 1**

Heat maps for CDTW clusters (A-D) which depict activity counts ranging from 0 counts/hour (cph) to > 1.2e5 cph (y-axis) for U.S. adults ages 20-65 y as drawn from NHANES 2003-2006 over a 24-hour day from time 0=12:00 to 24:00 the next day (x-axis). The proportion of the sample is indicated by the inverse gray-scale legend with 0.0% of the cluster participants to 12.6% of the cluster participants.

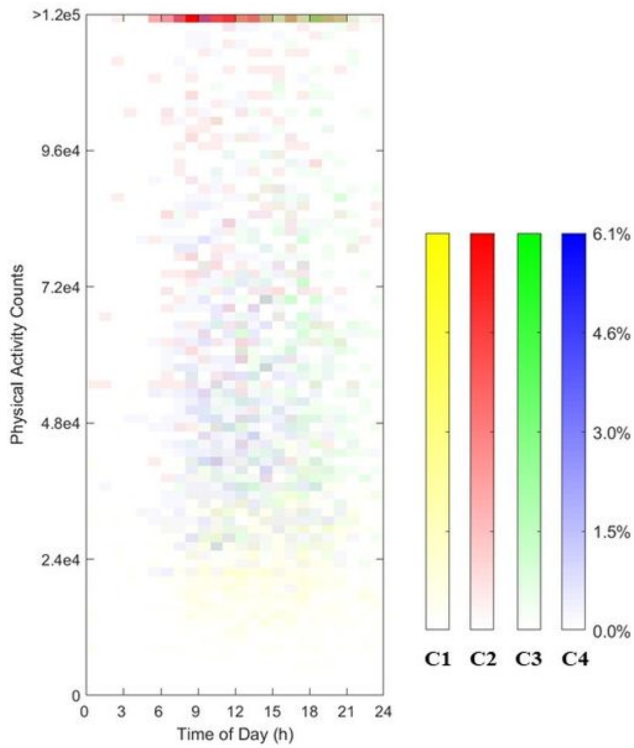


**Figure 2**

Heat maps for CDTW clusters (C1-C4) which depict the distribution of the largest activity occasion within each cluster for U.S. adults ages 20-65 y as drawn from NHANES 2003-2006. The activity counts ranged from 0 cph to >1.2e5 cph (y-axis) over a 24-hour day from time 0=12:00 to 24:00 the next day (x-axis). The proportion of the sample is indicated by the inverse color-scale legend with 0.0% of the cluster participants to 6.1% of the cluster participants.

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- STROBEchecklistcrosssectionalIJBNPA.doc
- AdditionalFile3.docx
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