Identifying and describing segments of office workers by activity patterns

Associations with demographic characteristics and objectively measured physical activity

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Abstract

Purpose – The purpose of this paper is to identify and characterize patterns of physical activity among office workers employed in largely sedentary occupations at a major health insurer located in the Southeastern USA.

Design/methodology/approach – The authors used latent class analysis to identify segments of office workers ($n = 239$) based on their self-reported activities of daily living and exercise behaviors. The authors examined the association of demographic characteristics with segment membership, and differences in accelerometer-measured weekly minutes of light and moderate-vigorous physical activity across segments.

Findings – The authors identified two segments and labeled them "exerciser" and "non-exerciser." Being female was associated with lower odds of membership in the "exerciser" segment (OR = 0.18; 95% CI = 0.06, 0.52), while those with at least a bachelor's degree were more likely to be in the "exerciser" segment (OR = 2.12; 95% CI = 1.02, 4.40). Mean minutes of moderate-vigorous physical activity per week were greater for the "exerciser" segment than the "non-exerciser" segment.

Practical implications – Based on this sample, the authors found that office workers in sedentary occupations were roughly equally divided and distinguished by their engagement in exercise-type behaviors. The findings underscore the need for innovative workplace programming that enhances activity opportunities particularly for those that are not likely to exercise.

Originality/value – A scarcity of research on activity patterns among office workers inhibits development of targeted worksite activity programming. The present research reveals two segments of workers with regard to their activity patterns and suggests ways for worksites to meet their unique needs.

Keywords Exercise, Workplace health, Workplace wellness, Health promotion, Public health

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Introduction

Promotion of physical activity is a key public health strategy for prevention of chronic disease (Warburton *et al.*, 2006). The health benefits of physical activity accrue over time to reduce incidence of obesity, type 2 diabetes, and other activity-related chronic disease (Reiner *et al.*, 2013). Despite the various protective effects of physical activity, many adults in the USA fail to engage in recommended levels of physical activity (Katzmarzyk *et al.*, 2017; Tucker *et al.*, 2011). The 2008 Physical Activity Guidelines for Americans recommend that adults engage in 150 minutes per week of moderate intensity, 75 minutes of vigorous intensity, or a combination of moderate-vigorous physical activity for 150 minutes per week (Physical Activity Guidelines Advisory Committee, 2008). However, recent self-reported data from the National Health Interview Study in 2016 suggest that only about half of adults meet aerobic guidelines (Katzmarzyk *et al.*, 2017; Ward *et al.*, 2013), and accelerometer-based estimates suggest that the prevalence of adherence to aerobic guidelines might be as low as 9.6 percent nationally (Tucker *et al.*, 2011).

Because physical activity encompasses activities of daily living (e.g. housework, childcare) as well as exercise behavior (e.g. cycling, running), there are numerous ways that adults can achieve recommended levels of physical activity (Physical Activity Guidelines Advisory Committee, 2008). Occupational physical activity also counts toward meeting physical activity guidelines; however, adults are increasingly employed in largely sedentary office-based occupations that require minimal physical activity. Indeed, the proportion of adults in the USA employed in a median moderate-intensity occupation (defined as a median intensity level of 3.0-5.9 METs) declined from 48 percent in 1960 to 20 percent in 2008 (Church *et al.*, 2011).

Office workers in largely sedentary occupations spend long, uninterrupted periods of time sitting while engaged in deskbound activities (Clemes *et al.*, 2014; Thorp *et al.*, 2012). Reliance on desks for execution of job-related tasks means that the opportunity for engaging in light (e.g. standing) and moderate-vigorous (e.g. brisk walking) intensity physical activity is usually minimal. In addition, research suggests that individuals employed in sedentary occupations may also opt for more sedentary activities in their leisure time (Clemes *et al.*, 2014). Approximately three-quarters of adults in office and administrative support occupations are estimated to engage in insufficient physical activity during leisure time to meet federal guidelines (Shaikh *et al.*, 2015).

Given the burden of insufficient physical activity, a variety of workplace physical activity interventions have been developed to enhance levels of physical activity and prevent chronic disease (Buckley *et al.*, 2015; Conn *et al.*, 2009; Malik *et al.*, 2014; Sorensen *et al.*, 2011; To *et al.*, 2013). These interventions span from individual-focused intensive aerobic exercise training interventions to organization-wide changes in built environment (e.g. walking paths) and policies (e.g. protected time for physical activity). Systematic reviews have found that worksite physical activity interventions are associated with improvement, though modest, in levels of physical activity and weight (Conn *et al.*, 2009; Malik *et al.*, 2014; To *et al.*, 2013).

While there has been a rapid proliferation of workplace physical activity programs among mid-to-large size employers (Mattke *et al.*, 2013), substandard levels of recruitment and participation limit the effectiveness of workplace interventions (Ryde *et al.*, 2013). Those efforts may be more successful in enrollment and impact if programs are designed to meet the needs of workers, with particular attention paid to the activity preferences of underlying worker segments (Marshall, 2004). Audience segmentation is a principle of social marketing that posits that populations are made up of underlying segments of people sharing similar preferences and behaviors (Forthofer and Bryant, 2000). A few studies have utilized audience segmentation to identify patterns of physical activity behavior in adult populations (Cheung *et al.*, 2015; Mooney *et al.*, 2015; Morrow-Howell *et al.*, 2014; Silverwood *et al.*, 2011), though none of these studies have examined segments of physical activity behavior among office workers.

The purpose of this study is to identify segments of office workers by examining their patterns of self-reported engagement in activities of daily living and exercise behavior. In addition, we examine if segments differ by demographic characteristics and weekly minutes of accelerometer-measured light and moderate-vigorous physical activity. The sample is composed of office workers in mostly sedentary occupations employed at a health insurer in North Carolina.

We set hypotheses with regard to the number of segments and associations with demographic characteristics and accelerometer-measured physical activity. We hypothesized that the number of activity behavior segments would range between two and four. A two-segment solution would primarily be differentiated by those that are highly active and highly inactive: usually engaged in both categories of activity (i.e. activities of daily living and exercise behavior); and usually engaged in neither category of activity. A four-segment solution would suggest that, in addition to highly active and highly inactive segments, there are also segments that usually engage in a certain category of activity but not the other: usually engaged in both categories of activity, usually engaged in neither category of activity, usually engaged in activities of daily living but not exercise behaviors, and usually engaged in exercise behaviors but not activities of daily living. Additionally, we hypothesize that segments with a greater number of activities reported usually engaged will be associated with greater weekly minutes of light and moderate-vigorous physical activity than segments with lesser number of activities usually engaged. Finally, we hypothesized that segment membership would differ by age, sex, race/ethnicity, marital status, educational attainment, children in household, and occupation.

Methods

Parent study

The present study is a secondary analysis of data collected from participants enrolled during the 12-month baseline phase (March 2015-March 2016) of the effects of physical activity calorie expenditure (PACE) food labeling (5R01CA184473) study. The study evaluated the effectiveness of PACE food labeling on meal calorie purchasing and physical activity levels among worksite cafeteria patrons at a major health insurer in North Carolina. PACE food labeling displays the number of miles of walking necessary for a prototypical adult (e.g. 160 lb adult walking at a 30 minute/mile pace) to burn off the calories contained in the labeled food. All ethical aspects were approved by the Institutional Review Board of the University of North Carolina at Chapel Hill. The present study uses data from the baseline phase of the trial before PACE food labeling was implemented; no intervention phase data are studied. Details on the parent study can be found elsewhere (Viera *et al.*, 2017).

The study was conducted in three worksites of a major health insurer in North Carolina employing approximately 3,600 workers. A cohort was recruited from each worksite through e-mail, company newsletter, cafeteria signage, and in-person recruitment tables. Full-time employees and contract workers were eligible for the PACE study if they were at least 18 years of age and reported eating lunch or were willing to eat lunch from the cafeteria at least three times per week. The study population was comprised of workers who self-reported an occupation in administrative/clerical, customer service/sales, financial/technical, environmental/food services and management categories. The sample that participated in this research consists of 414 participants that were enrolled into the parent study and invited to complete a variety of study-related questionnaires and measurements.

Measures

Activities of daily living and exercise behaviors. During April 2015-June 2015, all participants were invited to complete the Community Health Activity Model Program for Seniors (CHAMPS)

physical activity questionnaire. The CHAMPS questionnaire measured employees' participation in activities of daily living and exercise behaviors in the past week. The CHAMPS questionnaire was originally designed to assess the types, frequency, and duration of activity behaviors in which adults usually engage (Stewart *et al.*, 2001). We used a modified version of CHAMPS originally developed by Resnicow *et al.* (2003) which better matches the age and race/ethnicity composition of our sample. Because of measurement error in self-reported physical activity instruments (Colbert *et al.*, 2011; Hekler *et al.*, 2012), we did not use CHAMPS to estimate time spent in physical activity intensity levels or energy expenditure. Rather, CHAMPS was solely used to assess the types of activity behaviors that one usually performs. Of 414 participants in the baseline sample, 310 completed the CHAMPS questionnaire (74.9 percent response rate).

CHAMPS data examining the frequency of activity behavior engagement in the past week were dichotomized for analysis, an approach consistent with previous finite mixture modeling of self-reported adult physical activity data (Mooney *et al.*, 2015; Morrow-Howell *et al.*, 2014). The indicator variables were dichotomized by those that engaged in the behavior at least once in the past week (vs no engagement in the past week), except for frequently reported activities or behaviors with relatively high variance (e.g. leisure walking, light housework), which were dichotomized at the median. To ensure model parsimony, only CHAMPS activities that have been reported by at least 20 percent of the analytic sample were included. In the case of similar but separately measured activities (e.g. aerobics vs aerobic machine, light gardening vs heavy gardening), variables were combined and included if either sub-activity was endorsed by less than 20 percent of the sample, but exceeded 20 percent in combination. Of the 22 CHAMPS indicator variables considered (including those combined), a total of five activities of daily living and seven exercise behaviors ($n = 12$; 55 percent) met inclusion criteria.

Demographic characteristics and objectively measured physical activity. Demographic characteristics and objectively measured physical activity data were collected and used to compare the segments informed by the CHAMPS data. At enrollment, participants completed an in-person self-administered "Demographics and Brief Medical History" questionnaire on a mobile tablet (iPad; Apple Inc., Cupertino, CA). A study staff member was available to assist participants and provides a paper-based questionnaire in the event of any technological issues.

During July 2015-September 2015, all participants were invited to wear an accelerometer for objective measurement of light, moderate, and vigorous physical activity over seven consecutive days. Participants were provided an accelerometer (wGT3X-BT; Actigraph, LLC, Pensacola, FL) to wear over the right side of the hip throughout the day and night except for showering. Participants also received a pencil-and-paper log to record the date, bed times, and wake times. A $10 cash incentive was given to participants to encourage wearing the accelerometer for a week.

Accelerometers capture movement in the form of "counts" which are then processed into minutes of light physical activity and moderate-vigorous physical activity based on pre-specified cutpoints. Cutpoints originally developed for NHANES were used to define light (100-2,020 counts/minute) and moderate-vigorous (≥2,020 counts/minute) physical activity (Evenson *et al.*, 2015; Troiano *et al.*, 2008). Valid accelerometer data were defined as at least four days and approximately 8 hours of wear time per day (≥7.5 hours/day) (Harris *et al.*, 2015; Miller *et al.*, 2013). The minutes of physical activity per day were averaged and multiplied by 7 to create minutes per week variables for light and moderate-vigorous physical activity (Slootmaker *et al.*, 2009). Of 414 participants in the baseline sample, 240 contributed valid accelerometer-measured data (58.0 percent response rate). Most participants in the analytic sample provided valid accelerometer wear data ($n = 177$; 74.1 percent).

BMI. Between January 2015 and September 2015, a trained technician in the employer's biometric screening program used a portable stadiometer (213; Seca Ltd, Hamburg, Germany) and digital scale (WB-110A; Tanita Corp., Arlington Heights, IL) to take a single measurement of workers' height and weight, respectively. A continuous BMI variable was derived and rounded to the nearest tenth decimal place. Of 414 participants in the baseline sample, 284 had weight and height measurements for calculation of BMI (68.6 percent response rate). BMI was used as a covariate in analyses examining differences by segments.

Data analysis. All data management and analyses were performed with Stata (version 14; Stata Corp., College Station, TX) and Mplus (version 7.4; Muthén & Muthén, Los Angeles, CA). Variables were inspected for missingness, outliers, and distributional assumptions. A two-sided α of 0.05 was set for statistical significance.

To identify segments of office workers, we used the 12 selected activity behaviors as indicator variables in a latent class analysis. Latent class analysis is a person-centered quantitative approach to revealing underlying classes (or segments) of individuals based on the patterns of individual responses. In contrast to algorithm-based cluster analysis methods (e.g. signal detection analysis), it is based on a formal statistical model that allows the estimation of probabilities of membership in each class per individual, rather than assigning each individual to one class according to pre-defined criteria (as done in applications of cluster analysis). In this way, we account for the inherent uncertainty of classifying individuals into a single latent subgroup. For each class, conditional probabilities are estimated to show the likelihood that each class member engages in each activity behavior as dichotomized (i.e. engages in the behavior at least once per week).

To determine the true number (and patterning) of activity behavior classes, information criteria and statistical tests are used. In the present study, we used the Bayesian information criterion (BIC) and bootstrap likelihood ratio test (BLRT) to select the latent class solution. The BIC and BLRT have been shown to perform consistently well in selecting the true number of classes in sample sizes ranging 200-1,000 (Nylund *et al.*, 2007; Tein *et al.*, 2013). In addition to the BIC and BLRT, the entropy index value was calculated to describe the classification quality (i.e. extent of certainty that individuals are accurately classified) in each class solution. The preferred class solution has a low BIC value, significant BLRT statistic ($p < 0.05$), high entropy index value, and is interpretable (i.e. each class indicates a cogent pattern of activity behavior).

Once the class solution was selected, we used the Vermunt 3-step approach to assess how class membership was associated with demographic characteristics and accelerometer-measured weekly minutes of physical activity (Vermunt, 2010). The Vermunt 3-step approach is used to adjust for the uncertainty of assigning each individual to a class when estimating class associations with covariates. The Vermunt 3-step approach improves upon traditional classify-analyze approaches, which risk bias due to lack of adjustment for classification uncertainty (Bakk *et al.*, 2013; Vermunt, 2010). Applications of the Vermunt 3-step approach were used to examine demographic correlates and estimate class-specific means of weekly minutes of accelerometer-measured light and moderate-vigorous physical activity.

Demographic correlates of segment membership were evaluated using the automated R3STEP application of the Vermunt 3-step approach in Mplus. Multinomial logistic regression models were estimated to evaluate the odds of class membership vs a referent class by age, sex, race/ethnicity, marital status, educational attainment, children in household, and occupation.

Segment differences in mean accelerometer-measured minutes of light and moderate-vigorous physical activity per week were assessed using the manual Vermunt 3-step continuous distal outcome application. To account for departures from normality in

the outcome distributions, we freely estimated class-specific variances in the distal outcomes (Bakk and Vermunt, 2016). Wald tests of equality were performed to examine whether the class-specific mean estimates were significantly different. We estimated three types of models to assess potential influence of confounding: M1) crude, M2) demographics-adjusted, M3) demographics and BMI-adjusted.

In the analytic sample, there were no missing activity behavior indicator variable data. However, roughly one-quarter of included participants did not provide valid accelerometer data ($n = 62$; 25.94 percent) and were handled through the expectation-maximization algorithm (Blankers *et al.*, 2010). Due to missingness of demographic covariates, only two participants were deleted from analyses. Fixed effects were used to control for the clustering of workers in the three worksites.

Results

The analytic sample is comprised of baseline data from participants that were enrolled in the study ($n = 414$), including those that later withdrew from the PACE study. Of 414 participants, we excluded those that did not complete the self-reported physical activity questionnaire ($n = 104$) or have weight and height measured for BMI calculation ($n = 130$). In total, 59 participants were missing both self-reported physical activity and BMI data. Therefore, the analytic sample size is 239. The included participants were more likely to be older ($p = 0.003$), female ($p = 0.017$), and married or in domestic partnership ($p = 0.040$) than excluded participants.

Table I shows descriptive characteristics of the analytic sample. A majority of the sample was female ($n = 196$; 82.01 percent), earned at least a bachelor's degree ($n = 154$; 64.44 percent), and was married or in a domestic partnership ($n = 129$; 53.97 percent). About one-third of participants reported a financial or technical occupation ($n = 80$; 33.61 percent) while the rest were in a management ($n = 65$; 27.31 percent), customer service or sales ($n = 48$; 20.17 percent), or administrative or clerical occupation ($n = 45$; 18.91 percent). More than 80 percent of the sample was overweight or obese. Mean minutes of objectively measured moderate-vigorous physical activity per week were slightly lower than federal guidelines of 150 minutes per week (mean $= 144.30$ minutes; SD $= 111.10$). The prevalence of engagement in each selected activity behavior is shown in Table II.

Table III displays the BIC and BLRT results for each class (i.e. segment) solution examined: 2-class, 3-class, and 4-class. As the number of classes fit increased, the BIC value increased. The BLRT test statistic comparing k vs $k-1$ classes was statistically significant ($p < 0.0001$) for each model fitted, thereby indicating improved model fit for each class added. We selected the 2-class model as the preferred solution. The BIC value (3,502.46) was lowest of the three models, and the pattern of physical activity behavior suggested by each class was plausible. The entropy index value of the 2-class model (0.75) indicated that the model was sufficiently capable of classifying individuals into classes.

Table IV displays the prevalence of latent class membership by modal assignment (i.e. most likely class) and class-specific conditional probabilities of engaging in each activity behavior. The sample was roughly evenly divided with 50.2 percent of the sample belonging to the class deemed as representing "exercisers" and 49.8 percent belonging to the class labeled as representing "non-exercisers."

In the "exerciser" class, members were distinguished by a moderate probability of engagement in an array of exercise behaviors (0.39-0.60). Of all exercise behaviors, the "exerciser" class had the highest probability of engaging in light strength training (0.60) and stretching or flexibility exercises (0.58), while they were least likely to use a bicycle or stationary cycle (0.39). Of all activities of daily living, "exercisers" were most likely to engage in heavy housework (0.43) and light or heavy gardening (0.44), while least likely to engage in childcare (0.23) and light housework (0.38).

	n [mean]	% [SD]
Age (years)	[43.44]	[9.76]
Sex		
Male	43	17.99
Female	196	82.01
Race		
White	115	48.12
Black or African American	102	42.68
Asian	10	4.18
More than one race	7	2.93
Other	5	2.09
Hispanic		
No	228	95.40
Yes	11	4.60
Education		
Less than high school	0	0.00
High school	30	12.55
Some college	0	0.00
Technical or trade school	18	7.53
Associate's degree	37	15.48
Bachelor's degree	89	37.24
Master's or other advanced degree	65	27.20
Occupation[a]		
Administrative or clerical	45	18.91
Customer service or sales	48	20.17
Financial or technical	80	33.61
Environmental or food services	0	0.00
Management	65	27.31
Marital status		
Single, never married	60	25.10
Married or domestic partnership	129	53.97
Widowed	4	1.67
Divorced or separated	46	19.25
Number of children in household (< 18 yr)[b]	[0.88]	[1.05]
Body mass index (BMI)	[31.91]	[8.05]
Weight status		
Underweight (< 18.50)	1	0.42
Normal weight (18.50-24.99)	46	19.25
Overweight (25.00-29.99)	65	27.20
Obese ($\geqslant 30.00$)	127	53.14
Accelerometry[c]		
Moderate-vigorous physical activity per week (minutes)	[144.30]	[111.10]
Light physical activity per week (minutes)	[1,514.32]	[389.42]
Worksite		
A	88	36.82
B	89	37.24
C	62	25.94

Table I. Descriptive characteristics of analytic sample

Notes: $n = 239$. Missing values not included in calculation of percentages. [a]1 participant missing occupation information; [b]1 participant missing number of children information; [c]62 participants missing accelerometry information

	n	%
Activities of daily living		
Walk leisurely	101	42.26
Care for children	56	23.43
Light housework	94	39.33
Heavy housework	85	35.56
Light or heavy gardening[a]	95	39.75
Exercise behaviors		
Bicycle or stationary cycle using legs only	56	23.43
Aerobics or aerobic machine use[b]	72	30.13
Fast or brisk walking	83	34.73
Jogging or running	51	21.34
Light strength training	78	32.64
Moderate to heavy strength training	58	24.27
Stretching or flexibility exercises	89	37.24

Notes: $n = 239$. Activity behaviors are dichotomized by engagement at least once in the past week, except for walking leisurely and light housework, which were dichotomized at the median. Included activities were reported by at least 20 percent of the sample. [a]Combined light and heavy gardening; [b]combined aerobics/aerobic dancing and aerobic machine

Table II. Frequencies of activities of daily living and exercise behavior indicator variables

Classes	*n*	LL	BIC	*E*	BLRT LL	BLRT *P*	*C*1	*C*2	*C*3	*C*4
2	239	−1,677.30	3,502.46	0.746	−1,765.03	< 0.0001	120	119	–	–
3	239	−1,652.83	3,535.67	0.809	−1,677.30	< 0.0001	104	25	110	–
4	239	−1,630.80	3,573.76	0.826	−1,652.83	< 0.0001	28	111	72	28

Notes: $n = 239$. LL, log likelihood; BIC, bayesian information criterion; E, entropy; BLRT, bootstrap likelihood ratio test; C, number of participants in each class of solution. The two-class solution was selected as the preferred model representing the true class structure among office workers in the sample

Table III. Class enumeration fit statistics

In the "non-exerciser" class, there was low probability of engaging in any exercise behaviors (0.00-0.19). Of all exercise behaviors, "non-exercisers" were most likely to engage in fast or brisk walking (0.19) and least likely to engage in moderate to heavy strength training (0.00). Of activities of daily living, "non-exercisers" were most likely to engage in light housework (0.41) and walking leisurely (0.41), while least likely to engage in childcare (0.24). Notably, the probability of engaging in leisure walking, childcare, and light housework was roughly similar across classes.

Table V presents the odds of belonging to "exerciser" as compared to "non-exerciser" class for each demographic characteristic. Of all characteristics evaluated, educational attainment and sex were identified as key correlates of segment membership. Earning at least a bachelor's degree (vs educational attainment below a bachelor's degree) was associated with twice the odds of being in the "exerciser" class, as compared to the "non-exerciser" class (OR = 2.12; 95% CI = 1.02, 4.40). Meanwhile, being a female (vs male) was associated with significantly reduced odds of membership in the "exerciser" class (OR = 0.18; 95% CI = 0.06, 0.52) as compared to the "non-exerciser" class. Age, children in the household, occupation, race/ethnicity, and marital status were not statistically related to class membership.

Table VI shows how the two classes differed by levels of light and moderate physical activity objectively measured by accelerometer in three analytic models. With regard to

	Total sample	Exercisers	Non-exercisers
N	239	120	119
Class prevalence (%)		50.21	49.79
Activities of daily living			
Walking leisurely	0.42	0.43	0.41
Care for children	0.23	0.23	0.24
Light housework	0.39	0.38	0.41
Heavy housework	0.36	0.43	0.28
Light or heavy gardening	0.40	0.44	0.35
Exercise behaviors			
Bicycle or stationary cycle use	0.23	0.39	0.07
Aerobics or aerobic machine use	0.30	0.46	0.14
Fast or brisk walking	0.35	0.49	0.19
Jogging or running	0.21	0.41	0.01
Light strength training	0.33	0.60	0.03
Moderate to heavy strength training	0.24	0.47	0.00
Stretching or flexibility exercises	0.37	0.58	0.15

Table IV.
Prevalence of classes and conditional probabilities of activity behavior engagement

Notes: $n = 239$. Class N and prevalence based on most likely latent class membership of each observation (i.e. individuals assigned into class that she/he has highest probability of belonging). Activity behaviors are dichotomized by engagement at least once in the past week, except for walking leisurely and light housework, which were dichotomized at the median. Fixed effects for three worksites in all models

	"Exercisers" vs "Non-exercisers"				
	Coef.	SE	OR	95% CI	*P*
Age	−0.02	0.02	0.98	(0.94, 1.02)	0.275
Educational attainment[a]					
Bachelor's degree or above	0.75	0.37	2.12	(1.02, 4.40)	0.043
Sex[b]					
Female	−1.72	0.54	0.18	(0.06, 0.52)	0.002
Children in the household	0.34	0.40	1.40	(0.64, 3.05)	0.398
Occupation[c]					
Administrative or clerical	−0.54	0.53	0.58	(0.21, 1.64)	0.303
Customer service or sales	−0.11	0.54	0.90	(0.31, 2.57)	0.845
Financial or technical	−0.10	0.44	0.90	(0.38, 2.13)	0.814
Race/ethnicity[d]					
Non-Hispanic white	−0.06	0.38	0.94	(0.45, 2.00)	0.877
Marital status[e]					
Married or domestic partnership	−0.46	0.47	0.63	(0.25, 1.60)	0.333
Widowed, divorced, or separated	0.64	0.54	1.89	(0.65, 5.48)	0.239

Table V.
Correlates of membership to exerciser vs non-exerciser class

Notes: $n = 237$. Fixed effects for three worksites in all models. [a]Referent was below a bachelor's degree (high school, technical or trade school, associate's degree); [b]referent was male; [c]referent was management; [d]referent was Hispanic, Black or African American, Asian, more than one race, or other; [e]referent was single, never married

light physical activity, the total mean minutes of light physical activity ranged from about 1,486 to 1,542 minutes between classes and across analytic models. There were no statistically significant differences in light physical activity between the two classes in any of the models. For minutes of moderate-vigorous activity, the "exercisers" class had in

	Light physical activity			Moderate-vigorous physical activity		
	M1[a]	M2[b]	M3[c]	M1[a]	M2[b]	M3[c]
Log likelihood	−1,470.64	−1,454.31	−1,447.86	−1,196.05	−1,173.08	−1,163.59
Exercisers						
Mean	1,501.12	1,485.96	1,488.99	205.72	208.69	209.46
SE	41.66	42.47	41.51	13.42	13.48	13.52
Non-exercisers						
Mean	1,527.59	1,542.06	1,539.52	77.36	76.75	77.49
SE	47.91	48.38	47.35	4.31	4.16	4.04
P	0.70	0.42	0.45	< 0.001	< 0.001	< 0.001

Notes: $n = 237$. [a]Crude model: adjusted by worksite; [b]demographics-adjusted model: adjusted by worksite, age, education, sex, children in household, occupation, race/ethnicity, and marital status; [c]demographics- and BMI-adjusted model: adjusted by worksite, age, education, sex, children in household, occupation, race/ethnicity, marital status, and BMI

Table VI. Minutes of accelerometer-measured physical activity per week, per class

excess of 200 minutes of moderate-vigorous physical activity per week, on average, while the "non-exercisers" had less than 78 minutes of moderate-vigorous physical activity per week. Regardless of the adjustments used, "exercisers" had significantly more weekly minutes of accelerometer-measured moderate-vigorous physical activity than "non-exercisers."

Discussion

In the present research, we found two distinct segments of office workers based on their self-reported activities of daily living and exercise behaviors. Our findings are consistent with previous research identifying unique segments of adults that differ by their physical activity behavior (Cheung *et al.*, 2015; Mooney *et al.*, 2015; Morrow-Howell *et al.*, 2014). These studies suggest that population segments are primarily differentiated by the average intensity level of activities engaged (i.e. segments are primarily characterized by the extent to which moderate-vigorous activities are engaged), rather than the clustering of particular light and moderate-vigorous activities (e.g. segments are primarily characterized by permutations of engagement in specific light and moderate-vigorous activities).

Our research diverges from previous segmentation analyses in that only two segments were identified, rather than the five-to-six segments identified in studies of other adult populations (Cheung *et al.*, 2015; Mooney *et al.*, 2015; Morrow-Howell *et al.*, 2014). For example, a latent class analysis of adults in the Northern Manhattan Study identified six classes distinguished by the frequency of engagement in physical activity: no activity, rare activity, active weekly, active every other day, active daily, and highly active (Cheung *et al.*, 2015). Notably, these studies utilize large samples without exclusive focus on office workers. The fewer number of classes identified in the present study may be attributed to the homogeneity of the sample which included only sedentary office workers who were primarily overweight or obese. In addition, our smaller sample size may have restricted us from identifying additional segments.

We found that sex was significantly associated with segment membership. Female office workers were less likely to be in the "exerciser" class as compared to the "non-exerciser" class. Previous physical activity behavior segmentation research has found sex to be a significant correlate of segment membership, though the nature of the relationship is unclear. Nationally representative segmentation studies of adults in the UK and USA indicated that female sex was generally associated with membership in more active segments (Morrow-Howell *et al.*, 2014; Silverwood *et al.*, 2011). However, the relationship between sex and segment membership was less clear in segmentation studies of adults in

New York City (Cheung *et al.*, 2015; Mooney *et al.*, 2015). These conflicting findings suggest that the relationship between sex and segment membership potentially varies across adult subpopulations. Consequently, our findings might reflect barriers to physical activity that female office workers in sedentary occupations may experience more often than male peers in their daily life.

Aside from sex, educational attainment was the only other demographic characteristic significantly associated with segment membership. The association of educational attainment with activity behavior segment membership is consistent with previous segmentation research in the USA. Both Morrow-Howell *et al.* and Cheung *et al.* found that educational attainment was consistently related to membership in a more active segment (Cheung *et al.*, 2015; Morrow-Howell *et al.*, 2014).

The assessment of class-specific differences in accelerometer-measured weekly minutes of light and moderate-vigorous physical activity reflects how each behavioral pattern may result in different amounts of time spent in physical activity, and subsequent ability to meet physical activity guidelines. The "exerciser" class was associated with significantly greater minutes of moderate-vigorous physical activity per week than the "non-exerciser" class, exceeding national guidelines of 150 minutes of moderate-vigorous physical activity per week. Meanwhile, estimates of weekly minutes of light physical activity were largely identical, thereby reflecting the roughly equivalent engagement in light intensity sources of physical activity across classes (e.g. walking leisurely).

Limitations

Our findings must be considered along with their limitations. External validity is an important limitation. Our non-probability sample is composed of office workers employed by one health insurer across three North Carolina worksites, and primarily engaged in sedentary occupations: administrative/clerical, customer service/sales, or financial/technical. The prevalence of overweight and obesity in the analytic sample was higher than recent national and state-level adult prevalence estimates (Centers for Disease Control and Prevention, 2016; Ogden and Carroll, 2016), and limited data were available to draw inferences for normal weight or underweight individuals.

Participants that met inclusion criteria for this study were more likely to be older, female, and married or in a domestic partnership than those excluded. Therefore, the external validity of this research is additionally limited among the younger, male, and unmarried (or not in domestic partnership) individuals that provided insufficient data for inclusion in this study. Overall, these individuals composed a small proportion of the parent study in which this sample is drawn, and an even smaller proportion of the total workforce at these three worksites, indicating the need for robust recruitment strategies that enroll and retain young adults, men, and others that are consistently under-represented in workplace health interventions (Ryde *et al.*, 2013).

Self-report physical activity (April-June 2015) and accelerometry (July-September 2015) were not measured simultaneously. Though objectively measured physical activity was collected slightly after self-report physical activity, research shows that absolute levels of physical activity are largely stable throughout the year and only minimally affected by seasonal change (Hagströmer *et al.*, 2014; Martins *et al.*, 2017; O'Connell *et al.*, 2014; Wang *et al.*, 2017). Therefore, we do not expect levels of physical activity engagement to meaningfully differ across the two periods of measurement.

An existing workplace health program may have affected the segments found and may impact generalizability. The employer has a comprehensive workplace physical activity program offering multiple components including an individual-focused Weight Watchers program and organization-wide interventions, such as policies (e.g. sneakers allowed at work)

and environmental supports (e.g. on-campus gym facility). Therefore, our findings may be interpreted as identifying employee activity behavior segments that persist amidst prevailing comprehensive workplace physical activity programs.

Policy and practical implications

Our findings suggest that the promotion of activities that are accessible and enjoyable to the least active workers might be the best use of worksite resources, particularly when resources are limited. Specifically, worksite activity programs that support engagement in light activities of daily living may appeal to "non-exercisers" at the worksite, who may lack interest in moderate-vigorous exercise-type behaviors commonly targeted in workplace health promotion. For instance, walking was a commonly engaged activity across segments that is highly modifiable and associated with various health benefits (Hanson and Jones, 2015; Kassavou *et al.*, 2013). Systematic reviews show that walking group interventions are associated with a medium-sized positive effect on levels of physical activity and various beneficial health outcomes, including BMI, total cholesterol, blood pressure, and resting heart rate (Hanson and Jones, 2015; Kassavou *et al.*, 2013). Changes in workplace policies or built environment that support greater engagement in walking may therefore benefit workers that are otherwise uninterested in intensive moderate-vigorous exercise programs.

Conclusions

As more adults are employed in largely sedentary office occupations (Church *et al.*, 2011), information on the segmentation of office workers in sedentary occupations by activity patterns may become increasingly important in helping to design effective workplace physical activity programs. Our study found two segments of office workers suggesting differential likelihood of engagement in activity behaviors and levels of moderate-vigorous physical activity. Information on physical activity segments in the studied workplace provides valuable insight for researchers and practitioners targeting activity-linked chronic disease among sedentary office workers. The study fills a gap in the literature regarding patterns of physical activity among office workers in sedentary occupations, contributing evidence that office workers in sedentary occupations may be broadly distinguished by whether exercise behaviors are engaged in. Future research should explore how workplace wellness programs may effectively encourage "non-exercisers" to become more active, and therefore achieve greater impact.

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