

Original article

Longitudinal trajectories of physical activity in women using latent class growth analysis: The WIN Study

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Abstract

Purpose: This study aimed (1) to examine the longitudinal trajectories in objectively measured physical activity (PA); (2) to identify unknown (i.e., latent) subgroups with distinct trajectories; and (3) to examine the correlates of latent subgroups among community dwelling women.

Methods: The study sample included a total of 669 women from the Women's Injury Study, a 5-year prospective cohort study conducted from 2007 in the Southwest Central region of the US. Pedometer-based step-count data across 18 consecutive months were fitted to a latent growth model (LGM) and a latent class growth model (LCGM). Baseline characteristics were regressed on latent class membership.

Results: The longitudinal change in PA was best fit to a piecewise LGM with seasonal transitions. Significantly increased and decreased levels of PA were observed during the spring, fall, and winter, respectively ($p < 0.001$). Three latent subgroups with distinct PA trajectories were identified (low-active (46.8%), somewhat-active (41.3%), and active (11.9%)). Age and body fat percentage at the baseline significantly explained the likelihoods of being in low-active subgroup.

Conclusion: Seasonal variations in PA among women were observed but may not be practically significant. A relatively large portion of the sample showed low levels of PA for long periods. Intervention strategies should be considered for women who are overweight or obese, and aged >40 years old to promote PA during the life course.

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Keywords: Female; Pedometer; Prospective cohort; Season; Step-count

1. Introduction

Physical activity (PA) is a well-known modifiable lifestyle behavior that leads to better health in adults.¹ Specifically, a large body of literature demonstrate that compliance with current PA guidelines (i.e., ≥ 150 min of moderate-to-vigorous PA (MVPA) per week) is beneficially associated with health outcomes including but not limited to the reduced risk of developing cardiovascular disease,² type 2 diabetes,³ and cancer-related mortality.⁴ However, population-based estimates of adherence to PA guidelines demonstrated a low prevalence of U.S. adults attaining sufficient levels of PA to meet the recommendation, with women being less likely to be physically active than men.^{5–7} Such gender disparity in PA has been consistently observed from other population-based surveillance studies,^{8–10} and it is generally acknowledged that women may

experience distinct patterns of PA explained by different correlates from those of men.^{11,12}

Examining and describing a long-term PA pattern among women is therefore a pivotal first step in better understanding the variability in PA during the life course and identifying the risk groups who may experience long-term physically inactive lifestyle could impact future intervention strategies.^{10,12,13} However, a majority of PA research has used a cross-sectional, variable-centered approach within a scope of analytic epidemiology, in which the main focus is on the relationships of PA with health outcome variables. This approach may have a limited ability to extend our understanding of dynamic patterns of change in PA. Accordingly, a longitudinal study of PA in combination with variable- and person-centered analytic approaches is necessary to better describe the heterogeneity of longitudinal trajectories in PA across unknown (i.e., latent) subgroups.

The overarching goal of this secondary research is therefore to fill these gaps by applying a method that integrates

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variable- and person-centered analyses (i.e., latent class growth curve modeling (LCGM)) to the Women's Injury Study (WIN Study) data, which is a large prospective cohort study designed to examine long-term PA behaviors by tracking pedometer-based step counts among community-dwelling women. The specific aims were: (1) to describe longitudinal trajectories of objectively measured PA among women; (2) to identify the latent subgroups with different longitudinal trajectories; and (3) to examine the correlates of these latent subgroups based on participant characteristics. The findings from this study are expected to aid in the understanding of PA behaviors among women and the characteristics of potential groups of women at risk who should be targeted for future intervention.

2. Materials and methods

2.1. Survey and sample

Data for this research came from the WIN Study, a web-based, prospective open cohort study that primarily examined the incidence of musculoskeletal injuries in relation to PA behaviors among community-living women. Women aged ≥ 20 years were recruited between 2007 and 2008 from a listing of ≥ 6000 women in the Cooper Institute database. Additional recruitment was attempted throughout direct mail advertisement, health fair presentations, radio announcements, *etc.* Eligibility to participate in the WIN Study was determined throughout a pre-screening interview upon completion of informed consent. Women were excluded if they reported (1) any major disease or musculoskeletal conditions (e.g., heart-disease, cancer, physical injuries, or disabilities) requiring long-term medical treatments that limited their mobility or daily activities; and (2) needed of assistive device to ambulate. The inclusion criteria included women (1) who could perform regular daily, occupational, and recreational activities without being interfered by any disease or medical condition; (2) who could access a computer with Internet connection in a regular base; and (3) who had no plans to leave their residential area in the next 2 years. The women who met the inclusion criteria were monitored for up to 3 years.

The Cooper Institute's Institutional Review Board approved the WIN Study protocol, and details of WIN Study can be found elsewhere.^{14,15}

2.2. Pedometer step-counts

The participants were asked to wear an Accusplit 120XL-xBX (Accusplit Inc., Livermore, CA, USA) pedometer during waking hours for follow-up monitoring periods. The Accusplit 120XL-xBX pedometer uses the Digi-Walker internal engine to detect steps, and validity of the pedometer is previously reported.¹⁶ The participants reported the total number of steps taken and the number of days of pedometer-wearing for a 7- or 8-day interval via web-based surveillance. The login window was opened between Saturday 18:00 and Monday 24:00 to obtain the "real-time" measures of participant's PA. After completion of the web-based report, the participants were asked to reset the pedometer steps for continuous measures for the following week.

Weekly step-count data were used to calculate average steps/day in a month. Weekly step counts were considered invalid if (1) the wearing days (i.e., self-reported number of days wearing the pedometer during waking hours) were less than 4; and (2) the reported total step counts were < 3500 steps or $> 150,000$ steps in 1 week, and were excluded from the calculation.¹⁷ The steps/day in 1 week were averaged for each of 18 consecutive months to represent average steps/day in the respective months.

2.3. Baseline covariates

Baseline characteristics include (1) demographic variables (age (20–40 years, 41–60 years, and > 60 years), race (white and others), marital status (married/with partner and single), family income ($< \text{USD}50\text{k}$, $\text{USD}50\text{k}$ – $\text{USD}79\text{k}$, $\text{USD}80\text{k}$ – $\text{USD}99\text{k}$, $\geq \text{USD}100\text{k}$), employment status (employed and unemployed/retired)); (2) cardiovascular-related problems (yes and no); (3) bone-related problems (yes and no); and (4) percent body fat (%BF; normal, overweight, and obese).

Cardiovascular-related problems were determined by self-reported medication taken for heart disease, high blood pressure, high cholesterol, or peripheral artery disease. Women who responded "yes" to any item were considered having cardiovascular-related problems. Similarly, bone-related problems were determined by self-reported medication taking for osteoarthritis, rheumatoid arthritis, or low bone mass (osteopenia). Women who responded "yes" to any of these items were considered having bone-related problems.

%BF was estimated from skinfold measurements at 3 sites (triceps, suprailiac, and thigh) using the Jackson–Pollock equation.¹⁸ Women were classified into either normal, overweight, or obese using age- and gender-specific standards of %BF.¹⁹

2.4. Analytic sample

A total of 909 women provided weekly step counts for an average of 91.64 ± 36.04 weeks (median = 98.0) from the entry into the study. For current analysis, we purposefully selected the participants who provided valid average steps/day across 18 consecutive months between March, 2008 and August, 2009, with an allowance of 4 missing months (i.e., 18 data points with $< 25\%$ missing for each individual). This resulted in maximizing the analytic sample to 669 women (73% of the original sample) for the LCGM analyses, with 2.58% missing points (missing months: 311) from the entire data set (total observed months: $669 \times 18 = 12,042$).

2.5. Data analyses

The following steps were taken for data analyses. First, latent growth modeling (LGM) was applied to identify the best fit growth model for longitudinal trajectories of PA at an average level, which facilitated model specifications for subsequent analysis. Three LGMs with varying model specifications (linear, quadratic, and piecewise) were compared. For a piecewise model which is an alternative approach to capture the nonlinearity of growth trajectories,²⁰ 6 progressive linear slopes were specified with transitions at every 3 consecutive months

beginning from March. This also allowed us to explore the possible seasonal variability in objectively measured PA. We sought a best fit model based on lower values for sample size adjusted Bayesian information criteria (SABIC) and root mean square error of approximation (RMSEA), and higher values for comparative fit index (CFI) and Tucker–Lewis index (TLI). Second, the LCGM was further applied to the best fitted LGM model by taking into account the heterogeneity of growth parameters across latent subgroups. LCGM is a special case of the growth mixture model given the assumption of homogeneity of growth parameters within a latent subgroup.²¹ The number of latent subgroups was determined by comparison of models with 1–4 latent subgroups (denoted as k , the number of latent subgroup) based on empirical criteria including SABIC, a classification quality (entropy) estimated by posterior probability of class membership, and Lo–Mendell–Rubin likelihood ratio test (LMR-LRT). Lower values of SABIC, higher values of entropy (ranges between 0 and 1), and significant LMR-LRT that compared the model-data fit to a model with $k - 1$ latent subgroup indicate a better model for given k latent subgroups.²¹ Lastly, a multivariate multinomial logistic regression model was employed in which the latent subgroup was regressed on the set of baseline covariates using a logit link function. Odds ratios (OR) and associated 95% confidence intervals (CI) of being in a particular subgroup compared to the reference subgroup were estimated in relation to baseline covariates.

A robust full information maximum likelihood algorithm was employed for parameter estimations of LGM and LCGM models with missing data under the assumption of missing at random.²² SAS Version 9.3 (SAS Institute, Cary, NC, USA) and Mplus Version 7.2²³ (Muthén & Muthén, Los Angeles, CA, USA) were used for data management and analyses.

3. Results

3.1. Baseline characteristics

Table 1 compares the baseline characteristics of the analytic sample at the time of entry to the WIN Study with the samples that were excluded from the analysis based on the inclusion/exclusion criteria. In general, the analytic sample had higher proportions of women who are older than 40 years ($\chi^2 = 46.88$, $p < 0.001$), white ($\chi^2 = 18.01$, $p < 0.001$), married or living with partners ($\chi^2 = 15.54$, $p < 0.001$), have no bone-related problems ($\chi^2 = 6.15$, $p = 0.013$), and who have a normal %BF ($\chi^2 = 6.80$, $p = 0.033$). The median follow-up weeks were significantly greater for the analytic sample (104 weeks, interquartile range = 91.0–120.0) than those who were excluded (43 weeks, interquartile range = 16.5–81.0).

3.2. Model selections for LGM and LCGM

The piecewise LGM was best fit to data with the smallest SABIC (201,971.23) and RMSEA (0.075, 90%CI: 0.069–

Table 1
Baseline characteristics of analytic sample compared to excluded sample in the Women's Injury Study (WIN Study)

	Analytic ($n = 669$)	Excluded ($n = 240$)	p^b
Total follow-up weeks, median (IQR)	104.0 (91.0–120.0)	43.0 (16.5–81.0)	<0.001
Age, n (%)			<0.001
20–40 years	83 (12.41)	76 (31.67)	
41–60 years	394 (58.89)	119 (49.58)	
>60 years	192 (28.70)	45 (18.75)	
Race, n (%)			<0.001
White	541 (80.87)	162 (67.50)	
Others	128 (19.13)	78 (32.50)	
Marital status, n (%)			<0.001
Married/partner	447 (66.82)	126 (52.50)	
Single	222 (33.18)	114 (47.50)	
Family income, n (%)			0.074
<USD50k	153 (22.87)	73 (30.42)	
USD50k–USD79k	169 (25.26)	55 (22.92)	
USD80k–USD99k	122 (18.24)	32 (13.33)	
≥USD100k	225 (33.63)	80 (33.33)	
Working status, n (%)			0.113
Employed	445 (66.52)	173 (72.08)	
Unemployed/retired	224 (33.48)	67 (27.92)	
Cardiovascular-related problems, n (%)			0.438
Yes	194 (29.00)	76 (31.67)	
No	475 (71.00)	164 (68.33)	
Bone-related problems, n (%)			0.013
Yes	252 (37.57)	69 (28.75)	
No	417 (62.33)	171 (71.25)	
%BF, n (%) ^a			0.033
Normal	404 (60.39)	126 (52.50)	
Overweight	147 (21.97)	54 (22.50)	
Obese	118 (17.64)	60 (25.00)	

^a Age- and gender-specific standards of %BF were used for the classification.

^b χ^2 test of independence for categorical variables, and Kruskal–Wallis test for continuous variables with non-normal distribution.

Abbreviations: %BF = percent body fat; IQR = interquartile range.

Table 2
Underlying model selection for LGM.

	SABIC	RMSEA (90%CI)	CFI	TLI
Linear LGM	204,417.48	0.165 (0.160–0.170)	0.841	0.853
Quadratic LGM	203,728.09	0.146 (0.141–0.152)	0.878	0.884
Piecewise LGM ^a	201,971.23	0.075 (0.069–0.080)	0.973	0.970

^a A model with best model-data fits.

Abbreviations: CFI = comparative fit index; CI = confidence interval; LGM = latent growth model; RMSEA = root mean square error of approximation; SABIC = sample size adjusted Bayesian information criteria; TLI = Tucker–Lewis fit index.

0.080), and the highest CFI (0.973) and TLI (0.970) compared to linear and quadratic LGMs (Table 2). Follow-up piecewise LCGM indicated that a model with 3 latent subgroups best represented heterogeneity of growth trajectories of step counts over 18 consecutive months (Table 3; entropy = 0.977; and significant LMR-LRT in combination with non-significant LMR-LRT at 4 latent subgroup model).

The growth parameters estimated from the piecewise LGM and LCGM are presented in Table 4. On average, the estimated steps/day at baseline (March) was 6957.92 (SE = 116.50). Significantly increased trends were observed in the 1st spring ($\beta = 265.80$, SE = 39.80) and the 2nd spring ($\beta = 219.03$, SE = 22.73), whereas decreased trends were observed in the 1st fall ($\beta = -116.69$, SE = 24.12) and the 1st winter ($\beta = -147.63$, SE = 20.72). No statistically significant trends were observed during the 1st and 2nd summers.

Table 3
Determining the number of latent subgroups using the piecewise LCGM.

Latent class	SABIC	Entropy	LMR-LRT	
			$\Delta 2LL$	<i>p</i>
1	220,383.67	—	—	—
2	212,841.02	0.965	11,267.75	0.017
3 ^a	209,267.81	0.977	4390.99	0.010
4	207,548.47	0.962	1949.91	0.639

^a An optimal number of latent subgroup model with best model-data fits.

Abbreviations: $\Delta 2LL$ = the difference of 2 log likelihoods between models with *k* and *k* – 1 latent subgroups; Entropy = a quality of classification; LCGM = latent class growth model; LMR-LRT = Lo–Mendell–Rubin likelihood ratio test; SABIC = sample size adjusted Bayesian information criteria.

Table 4
Growth parameter estimates from the piecewise LGM and LCGM.

	<i>n</i> (%)	Intercept (SE)	Growth ^a					
			1st spring (3,4,5)	1st summer (6,7,8)	1st fall (9,10,11)	1st winter (12,1,2)	2nd spring (3,4,5)	2nd summer (5,6,7)
Piecewise LGM								
Full sample	669 (100)	6957.92 (116.50)*	265.80 (39.80)*	-17.04 (22.88)	-116.69 (24.12)*	-147.63 (20.72)*	219.03 (22.73)*	21.81 (22.90)
Piecewise LCGM^b								
Low-active	312 (46.64)	5017.20 (98.75)*	163.87 (45.15)*	-45.63 (24.62)	-83.95 (26.00)*	-114.36 (23.19)*	139.87 (24.30)*	27.09 (25.80)
Somewhat-active	277 (41.41)	8000.16 (155.16)*	337.19 (59.32)*	-51.23 (40.28)	-187.64 (39.86)*	-142.95 (31.88)*	300.35 (40.72)*	19.18 (41.88)
Active	80 (11.96)	11,297.36 (368.47)*	349.64 (147.91)*	125.19 (82.94)	9.48 (103.27)	-321.71 (92.48)*	247.06 (81.93)*	45.54 (83.45)

* *p* < 0.05.

^a The numbers in the parentheses indicate the corresponding months in each year; parameters are presented as β (SE).

^b A guideline suggested by Tudor-Locke and Bassett²⁴ was used for determining the profile of latent subgroups.

Abbreviations: LCGM = latent class growth model; LGM = latent growth model; SE = standard error.

Three latent subgroups identified from the piecewise LCGM included: (1) 312 women (46.64%) with an estimated baseline steps/day of 5017.20 (SE = 98.75); (2) 277 women (41.41%) with an estimated baseline steps/day of 8000.16 (SE = 155.16); and (3) 80 women (11.96%) with an estimated baseline steps/day of 11,297.36 (SE = 368.47). Growth trends of steps/day for each latent subgroup were generally aligned with the trends overall (increased in the 1st and 2nd springs; and decreased in the 1st fall and winter). The only difference observed in the 3rd latent subgroup was that no significant changes in steps/day were observed during the 1st fall ($\beta = 9.48$, SE = 103.27). Based on the information estimated from the piecewise LCGM, the profile of each latent subgroup was determined as “low-active” (5000–7499 steps/day), “somewhat-active” (7500–9999 steps/day), and “active” (10,000–12,499 steps/day), respectively.²⁴

3.3. Multivariate multinomial logistic regression with baseline covariates

The results of multinomial logistic regression with a logit link function predicting odds of being in low-active and active compared to somewhat-active are presented in Table 5. Middle-aged (41–60 years) and older (>60 years) women are more likely to be in low-active group (OR = 2.56, 95%CI: 1.41–4.66; and OR = 6.33, 95%CI: 3.11–12.86, respectively) than young women (20–40 years). Women who were overweight and obese at the time of entry were more likely to be in low-active than those who had a normal %BF (OR = 1.81, 95%CI: 1.19–2.76; and OR = 2.46, 95%CI: 1.52–3.99, respectively). In addition, women who reported having cardiovascular-related problems (OR = 0.33, 95%CI: 0.14–0.73) were less likely to be in active group.

4. Discussion

This study examined the longitudinal trajectories of objectively measured PA among community dwelling women. On average, we found that longitudinal changes in steps/day over 18 consecutive months were best presented in a model with seasonal transitions; steps/day significantly increased during spring and decreased during fall and winter. The variations in weather, temperature, and day time hours between seasons are commonly reported factors that may influence the level of PA;²⁵ our findings are generally aligned with previous reports which

Table 5
Multivariate multinomial logistic regression with baseline covariates.

	Low-active (<i>n</i> = 312, 46.64%)		Active (<i>n</i> = 80, 11.96%)	
	OR ^b	95%CI	OR ^b	95%CI
Age group (year)				
20–40	<i>Ref</i>	—	<i>Ref</i>	—
41–60	2.56	1.41–4.66	1.01	0.50–2.03
>60	6.33	3.11–12.86	0.67	0.24–1.75
Race				
White	<i>Ref</i>	—	<i>Ref</i>	—
Others	1.41	0.89–2.21	0.48	0.21–1.10
Marital status				
Married/partner	<i>Ref</i>	—	<i>Ref</i>	—
Single	1.01	0.68–1.50	0.76	0.40–1.45
Family income				
<USD50k	<i>Ref</i>	—	<i>Ref</i>	—
USD50k–USD79k	1.11	0.68–1.81	0.86	0.37–1.98
USD80k–USD99k	0.88	0.50–1.55	0.95	0.39–2.30
≥USD100k	0.74	0.45–1.24	1.01	0.45–2.12
Working status				
Employed	<i>Ref</i>	—	<i>Ref</i>	—
Unemployed/retired	0.84	0.56–1.26	0.95	0.53–1.69
Cardiovascular-related problems				
Yes	0.80	0.54–1.18	0.33	0.14–0.73
No	<i>Ref</i>	—	<i>Ref</i>	—
Bone-related problems				
Yes	0.99	0.68–1.45	1.04	0.58–1.87
No	<i>Ref</i>	—	<i>Ref</i>	—
%BF^a				
Normal	<i>Ref</i>	—	<i>Ref</i>	—
Overweight	1.81	1.19–2.76	0.48	0.21–1.07
Obese	2.46	1.52–3.99	1.06	0.49–2.25

^a Age- and gender-specific standards of %BF were used for the classification.

^b Adjusted OR of being low-active or active subgroups compared to somewhat-active subgroup (*n* = 277, 41.41%).

Abbreviations: %BF = percent body fat; CI = confidence intervals; OR = odds ratio; *Ref* = reference group.

showed significantly higher and lower levels of PA during spring and winter, respectively.^{26,27} However, the absolute seasonal changes in PA were less than 300 steps/day, which is not practically significant to impact on the overall level of PA in this population. The largest change identified was 265.80 steps/day (SE = 39.80) in the 1st spring, that is approximately a 4% increase when compared to estimated steps/day at baseline. One possible explanation for this finding relates to the nature of habitual PA behaviors among women. A large amount of daily PA in this population may be generally accounted by occupational and household activities^{13,28} that are less subjected to seasonal variations compared to the leisure-time PA. In the current analysis, the information regarding the specific domains of PA on which the step counts are accumulated was not available, limiting our ability to draw in-depth conclusions. Future study is warranted to explore the longitudinal patterns of domain-specific PA among women in order to better describe the diverse nature of PA across seasons.

We extended the findings from LGM by estimating the heterogeneity of growth parameters across latent subgroups. The results demonstrated the presence of 3 latent subgroups

(low-active, somewhat-active, and active), which have distinct trajectory patterns of PA. The patterns of seasonal changes in PA for each subgroup were generally consistent with the overall trend. The only difference observed was among the active subgroup in that the steps/day were not significantly decreased during the fall, whereas the other 2 subgroups are. This finding indicates that women in the active group are more likely to maintain their increased level of PA for a longer period compared to the other subgroups. However, as noted above, the changes in steps/day across seasons were not practically significant and tended to regress to the baseline values with relatively small magnitude of changes. In this point of view, the results imply that women who are physically inactive at the single measurement point may not change their level of PA for a long period, which may consequently impact health outcomes. In our analytic sample, a relatively large portion of women (46.64%) were estimated as low-active with baseline steps/day of 5017.20 and minimal variations across seasons (<±200 steps/day). This is far less than the recommended steps/day (7000–8000 steps/day) for adults to meet the current PA guidelines,²⁹ and therefore it becomes more crucial to identify the characteristics of women in this risk group who maintain low level of PA for a long period.

In the follow-up analysis for predicting subgroup membership using baseline covariates, we identified age and %BF as characteristics significantly explaining the likelihood of being low-active. Specifically, middle-aged and older women compared to young women, and overweight and obese women compared to women with normal %BF are more likely to be in low-active subgroup. Women experience unique body changes in the course of life, in which the alterations in sex hormone levels during the menopausal transition increase the risk of developing adverse health outcomes such as metabolic syndrome³⁰ and coronary heart disease.³¹ Moreover, abdominal adiposity is strongly associated with all-cause mortality including cardiovascular disease, and cancer among women,³² with women being more vulnerable to obesity than man.³³ Research identifies PA as a primary factor for healthy aging^{34,35} and for preventing obesity,^{1,3} with specific evidence for women.¹² PA is an effective lifestyle behavior that can potentially mediate the psychological and physical symptoms of menopause,^{36,37} the developments of menopause-related diseases,^{12,38} and abdominal adiposity.²⁸ Collectively the greater likelihood of maintaining low levels of PA among middle-aged and older women, and overweight and obese women have an important public health impact requiring public health action to develop and implement effective intervention strategies to promote PA among this population.

There are limitations that should be addressed when interpreting the findings of the current study. The participants of the WIN Study are incentivized and came from the relatively homogeneous population consisting of a majority of white, mid-upper class women within the same geographical area. The results therefore cannot be generalized to the entire women population residing in different areas. Furthermore, the length of measurement period (18 months) may not be sufficient enough to detect meaningful changes in PA behaviors among

this population. In addition, some of the baseline covariates (e.g., cardiovascular- or bone-related problems) were self-reported and thus are subject to recall bias. Nonetheless, this study is one of a few studies examining the longitudinal trends of PA among a relatively large sample of community dwelling women. Particularly, this study addresses the limitation of previous studies by incorporating variable- and person-centered approach for explaining the heterogeneity of longitudinal patterns of PA in this population. Moreover, the use of objectively measured PA by pedometers provided more reliable and valid estimate of PA over the measurement periods.

5. Conclusion

The findings of this study indicate that there is a seasonal effect that may influence PA among women; however, such changes may not be practically significant to understanding the changes in PA in this population. Importantly, the subgroup who was once physically inactive tends to maintain low levels of PA for a long period. Middle-aged and older women, and women who are overweight and obese are potentially at risk for participating in lower levels of PA and should be further targeted to promote PA during their life course. Future study is also warranted to examine the longitudinal patterns of domain-specific PA in varying environments to better understand the dynamic nature of PA among women with different socioeconomic statuses.

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Authors' contributions

YK, MK, and JRM conceived of the study; YK performed the statistical analysis and drafted the manuscript; YK, MK, AMT, and JRM interpreted the results and critically revised the draft. All authors have read and approved the final version of the manuscript, and agree with the order of presentation of the authors.

Competing interests

None of the authors declare competing financial interests.

References

- Haskell WL, Lee I, Pate RR, Powell KE, Blair SN, Franklin BA, et al. Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. *Circulation* 2007;**116**:1081–93.
- Shiroma EJ, Lee I. Physical activity and cardiovascular health: lessons learned from epidemiological studies across age, gender, and race/ethnicity. *Circulation* 2010;**122**:743–52.
- Sigal RJ, Kenny GP, Wasserman DH, Castaneda-Sceppa C, White RD. Physical activity/exercise and type 2 diabetes: a consensus statement from the American Diabetes Association. *Diabetes Care* 2006;**29**:1433–8.
- Kushi LH, Doyle C, McCullough M, Rock CL, Demark-Wahnefried W, Bandera EV, et al. American Cancer Society guidelines on nutrition and physical activity for cancer prevention. *CA Cancer J Clin* 2012;**62**:30–67.
- Tucker JM, Welk GJ, Beyler NK. Physical activity in U.S. adults: compliance with the physical activity guidelines for Americans. *Am J Prev Med* 2011;**40**:454–61.
- Troiano RP, Berrigan D, Dodd KW, Mâsse LC, Tilert T, McDowell M. Physical activity in the United States measured by accelerometer. *Med Sci Sports Exerc* 2008;**40**:181–8.
- Tudor-Locke C, Brashear MM, Johnson WD, Katzmarzyk PT. Accelerometer profiles of physical activity and inactivity in normal weight, overweight, and obese U.S. men and women. *Int J Behav Nutr Phys Act* 2010;**7**:60. doi: 10.1186/1479-5868-7-60
- Colley RC, Garrigué D, Janssen I, Craig CL, Clarke J, Tremblay MS. Physical Activity of Canadian adults: accelerometer results from the 2007 to 2009 Canadian Health Measures Survey. *Health Rep* 2011;**22**:7–14.
- Sisson SB, Katzmarzyk PT. International prevalence of physical activity in youth and adults. *Obes Rev* 2008;**9**:606–14.
- Brownson RC, Boehmer TK, Luke DA. Declining rates of physical activity in the United States: what are the contributors? *Annu Rev Public Health* 2005;**26**:421–43.
- Lee YS. Gender differences in physical activity and walking among older adults. *J Women Aging* 2005;**17**:55–70.
- Brown WJ, Burton NW, Rowan PJ. Updating the evidence on physical activity and health in women. *Am J Prev Med* 2007;**33**:404–11.
- Azevedo MR, Araújo CLP, Reichert FF, Siqueira FV, da Silva MC, Hallal PC. Gender differences in leisure-time physical activity. *Int J Public Health* 2007;**52**:8–15.
- Morrow Jr JR, DeFina LF, Leonard D, Trudelle-Jackson E, Custodio MA. Meeting physical activity guidelines and musculoskeletal injury: the WIN Study. *Med Sci Sports Exerc* 2012;**44**:1986–92.
- Bain TM, Frierson GM, Trudelle-Jackson E, Morrow Jr JR. Internet reporting of weekly physical activity behaviors: the WIN study. *J Phys Act Health* 2010;**7**:527–32.
- Schneider PL, Crouter SE, Bassett DR. Pedometer measures of free-living physical activity: comparison of 13 models. *Med Sci Sports Exerc* 2004;**36**:331–5.
- Morrow Jr JR, Bain TM, Frierson GM, Trudelle-Jackson E, Haskell WL. Long-term tracking of physical activity behaviors in women: the WIN Study. *Med Sci Sports Exerc* 2011;**43**:165–70.
- Jackson AS, Pollock ML, Ward A. Generalized equations for predicting body density of women. *Med Sci Sports Exerc* 1979;**12**:175–81.
- World Health Organization. Physical status: the use and interpretation of anthropometry. Report of a WHO Expert Committee, Technical Report Series No. 854.p.786–7, 1996.
- Flora DB. Specifying piecewise latent trajectory models for longitudinal data. *Struct Equat Model* 2008;**15**:513–33.
- Muthén BM, Muthén LK. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. *Alcohol Clin Exp Res* 2000;**24**:882–91.
- Little RJA, Rubin DB. *Statistical analysis with missing data*. 2nd ed. Hoboken, NJ: John Wiley & Sons; 2002.
- Muthén LK, Muthén BO. *Mplus user's guide*. 6th ed. Los Angeles, CA: Muthén & Muthén; 1998–2012.
- Tudor-Locke C, Bassett Jr DR. How many steps/day are enough? *Sports Med* 2004;**34**:1–8.
- Tucker P, Gilliland J. The effect of season and weather on physical activity: a systematic review. *Public Health* 2007;**121**:909–22.
- Kang M, Bassett DR, Barreira TV, Tudor-Locke C, Ainsworth BE. Measurement effects of seasonal and monthly variability on pedometer-determined data. *J Phys Act Health* 2012;**9**:336–43.
- Shephard RJ, Aoyagi Y. Seasonal variations in physical activity and implications for human health. *Eur J Appl Physiol* 2009;**107**:251–71.
- Kull M, Matsi J, Raudsepp L. Relationship between various physical activity domains and self-perceived health and obesity in women. *Women Health* 2010;**50**:639–51.
- Tudor-Locke C, Craig CL, Brown WJ, Clemes SA, De Cocker K, Giles-Corti B, et al. How many steps/day are enough? For adults. *Int J Behav Nutr Phys Act* 2011;**8**:79. doi: 10.1186/1479-5868-8-79

30. Janssen I, Powell LH, Crawford S, Lasley B, Sutton-Tyrrell K. Menopause and the metabolic syndrome: the study of women's health across the nation. *Arch Intern Med* 2008;**168**:1568–75.
31. Mondul AM, Rodriguez C, Jacobs EJ, Calle EE. Age at natural menopause and cause-specific mortality. *Am J Epidemiol* 2005;**162**: 1089–97.
32. Zhang CL, Rexrode KM, van Dam RM, Li TY, Hu FB. Abdominal obesity and the risk of all-cause, cardiovascular, and cancer mortality sixteen years of follow-up in US women. *Circulation* 2008;**117**:1658–67.
33. Ryan D. Obesity in women: a life cycle of medical risk. *Int J Obes (Lond)* 2007;(Suppl. 2):S3–7.
34. Peel NM, McClure RJ, Bartlett HP. Behavioral determinants of healthy aging. *Am J Prev Med* 2005;**28**:298–304.
35. Burke GL, Arnold AM, Bild DE, Cushman M, Fried LP, Newman A, et al. Factors associated with healthy aging: the cardiovascular health study. *J Am Geriatr Soc* 2001;**49**:254–62.
36. Nelson DB, Sammel MD, Freeman EW, Lin H, Gracia CR, Schmitz KH. Effect of physical activity on menopausal symptoms among urban women. *Med Sci Sports Exerc* 2008;**40**:50–8.
37. McAndrew LM, Napolitano MA, Albrecht A, Farrell NC, Marcus BH, Whiteley JA. When, why and for whom there is a relationship between physical activity and menopause symptoms. *Maturitas* 2009;**64**:119–25.
38. Peters TM, Schatzkin A, Gierach GL, Moore SC, Lacey Jr JV, Wareham NJ, et al. Physical activity and postmenopausal breast cancer risk in the NIH-AARP diet and health study. *Cancer Epidemiol Biomarkers Prev* 2009;**18**:289–96.