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Gender difference in “second-shift” physical activity: New insights from analyzing accelerometry data in a nationally representative sample

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A R T I C L E I N F O

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A B S T R A C T

The gendered organization of daily activities results in differential contexts of physical activity (PA) for the working population, especially during the “second shift” – a time window dominated by household-based activities. Existing research predominantly relies on self-reported leisure-time activities, yielding a partial understanding of gender difference in the source, timing, and accumulation pattern of PA. To address these limitations, this study draws on the interplay between work and family to understand how they shape gender difference in household-based PA across occupational groups. It combines work schedule and accelerometry PA data from the 2005–2006 National Health and Nutrition Examination Survey (NHANES), which permits our study of second-shift PA on workdays among full-time workers, aged 20 to 49, with a regular daytime schedule. To capture different aspects of second-shift PA, the PA outcomes are measured as both volume and accumulation patterns during time windows following (i.e., 6pm–9pm) and prior to typical working hours (7:30am-8:30am). Using generalized estimating equations, we estimate gender differences in the volume and fragmentation of second-shift PA. Overall, women with a full-time job exhibit both higher volume and higher fragmentation of second-shift PA than their male counterparts. The occupational group moderates such gender difference in PA. The gender gaps in PA volume and fragmentation are only evident for professional workers, whereas the second shift represents a gender-neutral context for PA accumulation for non-professional groups. These findings are supported by a secondary analysis when analyzing the whole-day PA data using functional data analysis. Such social patterning of second-shift PA calls for further research on gendered PA under the interplay of work and family beyond the usual focus on leisure activities.

1. Introduction

Gender has been widely acknowledged as a social determinant of inequality in health and health-related behaviors (Bird, 1999). However, little research addressing gender difference in physical activity (PA) has carefully contextualized how gendered organization of both work and family domains conflate to determine opportunities for PA accumulation. The narrow definition of PA, primarily as leisure-time activity, also hinders a thorough understanding of PA sources from other activity domains taking up the vast majority of waking hours. As such, the understanding of gender difference in PA is contained in the body of empirical evidence suggesting women’s disadvantage in leisure-time PA relative to men. Not until recently have researchers investigated sociodemographic patterning of domain-specific PA. This study extends to PA accumulated from the “second shift” time window, a concept counterposed to the paid work (“first shift”) (Hochschild & Machung, 1989). To do so, we focus on a sample of full-time workers from National Health and Nutrition Examination Survey (NHANES) 2005–2006 – the only wave that the work and family segments of the day can be determined by information on work schedule.

Given the associations between PA and health and the prevalence of physical inactivity, it is important to understand the sources of PA for effective public health recommendations (Warburton & Bredin, 2016). However, our current understanding of sociodemographic patterning of PA is mainly from large-scale health surveillance surveys focusing on self-reported leisure-time activities, which indicate that women are less

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active than men (Carlson et al., 2009). While recent researchers have increasingly used accelerometer-based measures to study gender differences in PA (Guthold et al., 2018), they typically studied PA throughout the day, which did not distinguish socially organized time windows that have differential PA accumulation opportunities for men and women. Thus, one further step is needed to understand why there are gendered patterns in PA and how they are associated with gendered organization of work and family activities. Indeed, accelerometer-based PA data afford richer opportunities to examine how PA is accumulated from socially meaningful time windows such as work hours (Yu et al., 2022) and non-working hours, which we refer to as second-shift time window due to its conceptual significance within the extensive literature of gender inequality (England, 2010; Usdansky, 2011).

Building on the principle of the interplay between work and family spheres (Clawson & Gerstel, 2014; Usdansky, 2011), we condition second-shift PA on the "first shift," described with broad categories of occupation (i.e., professional vs. non-professional) with varying PA intensities during working hours among full-time workers with a regular daytime schedule. Under this broader perspective, we apply the theoretical account in second-shift literature to the observed gender patterns of PA outside of working hours. Our study examines: (1) To what extent do women and men differ in the second-shift PA among full-time workers? (2) How are gender differences in second-shift PA moderated by the first shift? Answers to these questions will offer new evidence on social determinants of PA and, indirectly, health.

2. Literature review

Our current understanding of gender differences in PA is limited by the way PA is measured and a lack of theoretical consideration of gendered context of daily activities. This section provides a brief review and identifies the major knowledge gaps to be addressed in the paper.

2.1. Current knowledge of gender difference in PA

First, PA is usually narrowly defined as leisure-time activities using self-reported measures collected in large-scale health surveillance surveys. In this line of research, respondents are asked to recall whether and how much time they spent in predefined leisure-time activities in the past 30 days. The major finding is that women are consistently found to be less active than men (Carlson et al., 2009). However, focusing on leisure-time PA may not accurately capture the full extent of gender differences in PA, particularly in other domains such as work and housework (Cusatis & Garbarski, 2018; Smith et al., 2014). Collecting leisure-time PA is also subject to a substantial underestimation of activities that can be counted as PA, e.g., light-to-moderate intensity activities (Saint-Maurice et al., 2021). For instance, when survey participants are primed to consider PA from multiple activity domains (leisure, house/care work, and paid work), the amount of self-reported weekly PA increases significantly, from 262 min of leisure-only PA to 861 min of all-domain PA (Cusatis & Garbarski, 2018).

To gain a more complete picture of PA sources, another line of research has expanded to measuring PA in other activity domains, e.g., paid work and housework, without relying on direct survey questions. One leading effort is to link American Time Use Survey (ATUS) to the Compendium of Physical Activity, which assigns each documented primary activity a metabolic equivalent (MET) value to gauge PA intensity throughout 24 h (Tudor-Locke et al., 2009). Research based on the ATUS-MET data points out that leisure-time PA comprises only a very small portion of overall daily PA and gender differences may vary across activity domains (Cusatis & Garbarski, 2019; Saffer et al., 2013). For example, Cusatis and Garbarski (2019) used ATUS-MET data to classify three types of PA, i.e., leisure, house/care work, and paid work, and found that women indeed spent more time on house/care work PA than men. Focusing on non-work PA, Saffer et al. (2013) examined gender differences in four activity domains, including leisure, active travel, home, and other PA. They found that men have more leisure and active travel PA while having lower levels of home and other non-work PA than women. These findings clearly illustrate the importance of bringing in non-leisure activity domains to examine gender pattern in PA.

The ATUS-MET data, despite its advantage of distinguishing activity domains for PA, share some common limitations with self-reported PA measures. First, ATUS uses a day-reconstruction method, which asks respondents to recall activities on the day prior to the interview date. The duration of each activity may be inaccurate due to recall bias (Prince et al., 2008). Moreover, assigning an average MET value to an activity may not capture PA driven by two simultaneous activities or account for individual variance in energy consumption (Tudor-Locke et al., 2009). Accelerometry PA data collected in free-living environment addresses the issue of subjectivity and misclassification of PA intensity. To extend the understanding of PA sources previously relied on self-reported time-use data (e.g., Tudor-Locke et al., 2009), recent studies have increasingly used wearable accelerometers to provide objective, high-resolution data for PA intensity and timing (Leroux et al., 2019). Accelerometry PA data allows researchers to capture objective PA patterns and identify socially meaningful time window to study domain-specific PA, such as occupational PA during working hours (e.g., 9am to 5pm as in Yu et al., 2022). Integrating the dimension of timing also affords the opportunities to investigate diurnal patterns of PA accumulation patterns and link PA to socially organized time use patterns.

The second concern of understanding gender gap in PA pertains to the conceptualization of gender in empirical research. Although extending to activity domains beyond leisure to understand gender gap in PA has been fruitful, past research often includes gender as a demographic measure without considering the social context within which gender plays a role in determining health behaviors. This lack of reference to gender theories leads to *"replicating previously known gender differences in health status rather than explain their origin"* (Hammarström & Hensing, 2018, p. 17). Mindful of this research gap, we conceptualize the second shift (i.e., unpaid domestic work) as a key social context for gender gap in PA. More importantly, we consider how the social stratification by occupation in the first shift imposes differential opportunities and constraints for women and men to accumulate PA in the second-shift time window.

2.2. Theoretical consideration and hypotheses

The term second shift powerfully characterizes women's higher share of unpaid domestic labor outside their paid jobs than men's (Hochschild & Machung, 1989). The authors quantified the total amount of labor in terms of time that *"adding together the time it takes to do a paid job and to do housework and childcare … Most women work one shift at the office or factory and a second shift at home"* (Hochschild 1989, pp. 3–4). Later time-use research has lent supportive evidence to the gender gap in unpaid work (Bianchi et al., 2012). Although economic resource is conceptualized as a bargaining power in terms of cutting back housework, it explains little of gender difference in time spent on second-shift tasks (Hook, 2017). Recent theoretical work has shown that, while women are increasingly participating in the labor market, men are less quick to undertake female-typical activities, no matter in the workplace or at home (England, 2010). In addition to the unequal division of domestic labor within heterosexual unions, housework functions in a way of reinforcing gender norms for the unpartnered. For instance, pervious research shows that women do more housework than men regardless of marital status (South & Spitze, 1994). For this reason, we focus on gender and consider both partnered and unpartnered adults in our analysis.

Given that gender continues to be one of the most influential organizing principles of paid and unpaid work above and beyond individual resources, we make a case that second shift provides an important context for gender-based opportunities for PA accumulation. The timeconsuming routine housework (e.g., cooking and cleaning), often denoted as female-typical, contributes to the lion's share of PA in the second shift (Smith et al., 2014). For full-time workers with a regular daytime schedule, we expect that women are more physically active than their men counterparts in various measures of objective PA during the second shift (**Hypothesis 1**).

Going beyond the gender differences in second-shift PA due to unequal division of domestic labor, a further theoretical consideration lies on their structural constraints. A dominating constraint is theorized to be the paid work in the first shift. Hochschild and Machung (1989) suggested that the gendered division of housework is affected by broader inequalities, including gender-structured opportunities and barriers in the labor market. Since the first edition of Hochschild's influential book, women have made an impressive inroad into the higher education and this has opened up professional occupation opportunities to college-educated women (Xie & Shauman, 2005). Social stratification by occupation, e.g., professional vs non-professional, affects the life chances of workers and their families (Weeden & Grusky, 2005). Researchers are increasingly noticing that the gendered division of household labor is shaped by organizational constraints in paid work that differ between professional and non-professional occupations (Ferree, 2010; Usdansky, 2011).

Within professional occupations, men enjoy greater opportunities while women face greater barriers in climbing up the career ladder – the well-known glass ceiling effect favoring men's career development (Cotter et al., 2001). This structural constraint is found conductive to professional women being "pushed out" of the normal career ladder especially when they become mothers (Ishizuka & Musick, 2021) and have young children at home (Percheski, 2008). With disadvantaged payoff from the career line, women are more likely to prioritize family obligations than men in professional and managerial occupations (Clawson & Gerstel, 2014). As some have argued, the gender egalitarianism ideal is unattainable for upper- and middle-class workers, a phenomenon termed as "spoken egalitarianism" (Usdansky, 2011). Moreover, unsupportive work-family policies limit workers' choices in balancing responsibilities in both domains, which consequently impedes the formation of egalitarian relationships (Pedulla & Thébaud, 2015).

In contrast to workers in professional occupations, non-professional workers are confronted with a different set of constraints in institutional structures. These workers, who are often lower-income, are less likely to afford "opting out" or reducing paid work for family needs (Pedulla & Thébaud, 2015). In addition to financial strains, both women and men in non-professional occupations are likely to live with precarious working conditions. The schedule inflexibility is cited as a major structural constraint that necessitates working-class couples to alternate turns in fulfilling family obligations (Clawson & Gerstel, 2014). Some qualitative work shows that working-class fathers participate in daily childcare more often than upper-middle-class fathers (Shows & Gerstel, 2009). In contrast to professional workers, the strategies employed by working-class families to resolve the shortage of money and time conflict are likely to yield a pattern of equal contribution of both paid and unpaid labor, a phenomenon termed as "lived egalitarianism" (Usdansky, 2011).

This reasoning has led to our second hypothesis. Working women's greater share in the second-shift tasks is contingent upon their occupations. Given the occupation-specific structural constraints, we expect that the gender difference in the second-shift PA is more pronounced for professional occupations than for non-professional occupations (**Hypothesis 2**).

Finally, rising levels of sedentary work in recent decades have made increasing PA one of the leading public health challenges (Du et al., 2019). Previous research has shown that moderate-to-vigorous leisure-time PA is strongly associated with a wide range of health outcomes including mortality, cardiovascular disease, and diabetes (Prince et al., 2021), while the housework PA may not confer equivalent health benefits (Abu-Omar & Rütten, 2008; Lawlor et al., 2002). Therefore, it is crucial to identify groups at high risk of PA insufficiency and to understand causes of unequal opportunities for health-appropriate PA. Moreover, contextualizing PA helps unpack the complex housework-health relationships. For instance, long hours of housework may crowd out time for recovery (Adjei & Brand, 2018) and multitasking housework is related to higher level of stress (Offer & Schneider, 2011). Bringing in PA in the second shift contributes to a more contextualized understanding of PA-health link.

Considering the conceptual importance of domain-specific activity under gendered organization of work and family and desirable feature of objective PA measures, this study utilizes information on work schedule to focus on PA accumulated during the second shift, a time window dominated by household-related activities among full-time workers. Our study improves previous research in three ways. First, our approach is conceptualized in the broader social organization of time and activity, which improves upon the objectively measured daily PA volume regardless of the activity domains (Troiano et al., 2008). Second, it also extends the previous work on the social determinants of PA in the dominant domain of paid work (Yu et al., 2022) by conditioning PA in the second shift on the paid work. Third, we improve measurement by creating indicators of PA accumulation pattern, e.g., how often a person shifts between non-active and active status (technically termed fragmentation), which has unique health implication above and beyond PA volume (Di et al., 2017).

3. Data and methods

3.1. Data and sample

The National Health and Nutrition Examination Survey (NHANES) is a nationally representative survey that assesses health and nutritional status of adults and children in the United States through both household interview and medical/physical examinations. For this study, we draw data from the NHANES 2005–2006 wave (n = 10,348), which collects physical activity data using accelerometer-based PA monitors (https://wwwn.cdc.gov/Nchs/Nhanes/2005-2006/PAXRAW_D.htm) and has questions related to work schedule. Although the accelerometry data are also available in NAHNES 2011–2014, these waves do not survey participants on work schedule, precluding the ability to distinguish first-shift and second-shift PA using our methodology.

Physical activity monitoring data. The NHANES 2005–2006 wave collects activity data using ActiGraph AM-7164, a hip-worn uniaxial accelerometer that estimates locomotion. Respondents aged 6 and older are asked to wear the device for seven consecutive days during awake time. Raw sub-second acceleration data are summarized in minute-level epochs referred to as activity counts by NHANES. In this study, we use minute-level activity count and wear flag to construct PA summary measures using R package *rnhanesdata* (Leroux et al., 2019) for weekday non-sleeping minutes in the two selected time windows following and prior to the typical daytime 9pm-to-5pm work schedule, i.e., 6pm–9pm and 7:30am-8:30pm.[1]

Analytic Sample. We define our analytic sample as full-time workers on a regular daytime schedule to locate meaningful second-shift time windows. We base on employment-related questionnaire responses to create a sample whose working hours may reasonably be assumed to be similar across participants. Workers with alternative schedules are not considered due to the uncertainty of their second-shift time window. Besides, part-time workers are excluded because we cannot determine their second-shift time window without knowing their detailed weekly and daily work schedules. Specifically, we restrict our sample to full-time employed adults (age 20–49, as the major active age range of work and family arrangements) working on a "regular daytime schedule," which is normally arranged from 9am to 5pm on weekdays in

[1] Sensitivity analyses on the evening time range support its robustness.

industrialized countries (n = 1101). Additionally, we exclude respondents who report working over 50 h to the question "hours worked last week at all jobs" (n = 920). Finally, we include those who complied with the protocol of daily and evening wear of the PA monitor. We first follow the existing recommendation to include respondents who wear the PA monitor for at least 10 h per day (Leroux et al., 2019), and further exclude days with fewer than 2 h of wear time between 6pm and 9pm on weekdays. Finally, only respondents who have at least 2 such eligible weekdays are kept in the analytic sample (n = 614, with 2338 person-weekdays). A detailed sample selection process is presented in Appendix Figure A1. The analytic sample (n = 614) and the larger sample without applying the selection criteria of wear time (n = 920) have similar distribution of demographic characteristics except that women's share is slightly greater than the larger sample (Appendix Table A2).

3.2. Measures

Outcome Variables. We select 6pm–9pm as the primary observation window for the second shift. The justification is three-fold: (1) we choose 6pm as the starting point to allow for 1 h of post-work commuting time for "9-to-5" workers considering that commuting involves active PA, (2) we choose 9pm as the ending point because housework may slow down in many households, implied by the fact that the percentage of respondents wearing the PA monitor dropped notably after 9pm, and (3) 6pm–9pm is a usual family time window, especially for families with young children. We also select 7:30am-8:30am as an additional time window for activities such as preparing breakfast and lunch to depict a more complete picture of gender differences in second-shift PA. Choosing this relatively narrow morning observation window is due to the low percentage of respondents wearing PA monitor before 7:30am. Specifically, less than a quarter of person-weekdays are observed to wear PA monitor at 6:00am (Figure A2). We construct three PA summary measures for the 6pm–9pm window and one for 7:30am-8:30am window. The first outcome variable is total log-transformed activity counts (TLAC) to measure PA volume. The logarithmic transformation can yield a closer reflection of light-to-moderate intensity PA (Varma et al., 2018) – a level at which much housework is performed, and minimize the influence of moderate-to-vigorous activities predominantly contributed by physical exercise. As such, $TLAC_{6pm\text{-}9pm}$ is a plausible proxy for PA generated by household-related activities. Second, we include a fragmentation measure – sedentary to active transition probability (SATP), which is calculated as the inverse of average duration of sedentary bouts (Di et al., 2017). A sedentary bout is defined as a period lasting for at least 1 min in sedentary state (activity count ranges between 0 and 99). A higher value of SATP indicates greater likelihood of transitioning out of sedentary state. This measure complements $TLAC_{6pm\text{-}9pm}$ by providing additional information on PA accumulation pattern, i.e., the degree to which the accumulated PA is interrupted. Third, we add the count of sedentary bouts lasting at least 30 min to capture prolonged sedentary behaviors in the evening. Because of the short duration of morning time window, i.e., 1 h, only $TLAC_{7:30am\text{-}8:30am}$ is calculated. In the functional data analysis (detailed later), the outcome variable is minute-level log-transformed activity count (LAC) over the 24-h day.

Main Explanatory Variables. Gender is coded as a binary variable: female (1) and male (0). NHANES 2005–2006 does not provide information on multi-gender categories. Occupational group is classified into three groups according to two characteristics, professional vs. non-professional and the binary intensity of occupational PA (OPA) with 0 for low-to-moderate and 1 for high. The professional occupations include 10 broad Standard Occupation Classification (SOC) categories (see Appendix Table A1) and the remaining 12 categories are coded as non-professional occupations. The OPA is coded according to a previous study based on the NHANES 2005–2006 (Yu et al., 2022) to distinguish occupations with different OPA levels. Since no professional occupation has high OPA, there are three occupational categories: (1) professional, low-to-moderate OPA, (2) non-professional, low-to-moderate OPA, and (3) non-professional, high OPA.

Control Variables. We include four sets of control variables. The demographic variables are race/ethnicity and age at examination. Race/ethnicity is coded into four categories as non-Hispanic White, non-Hispanic Black, Hispanic and non-Hispanic other. We consider two indicators of socioeconomic status: having a college degree and family income to poverty ratio. The third set of control variables are family-related characteristics: marital status (1 = married/cohabiting) and an interval variable of family size (top-coded at 7). We also control for the total wear time specific to each observation window in the regression analysis.

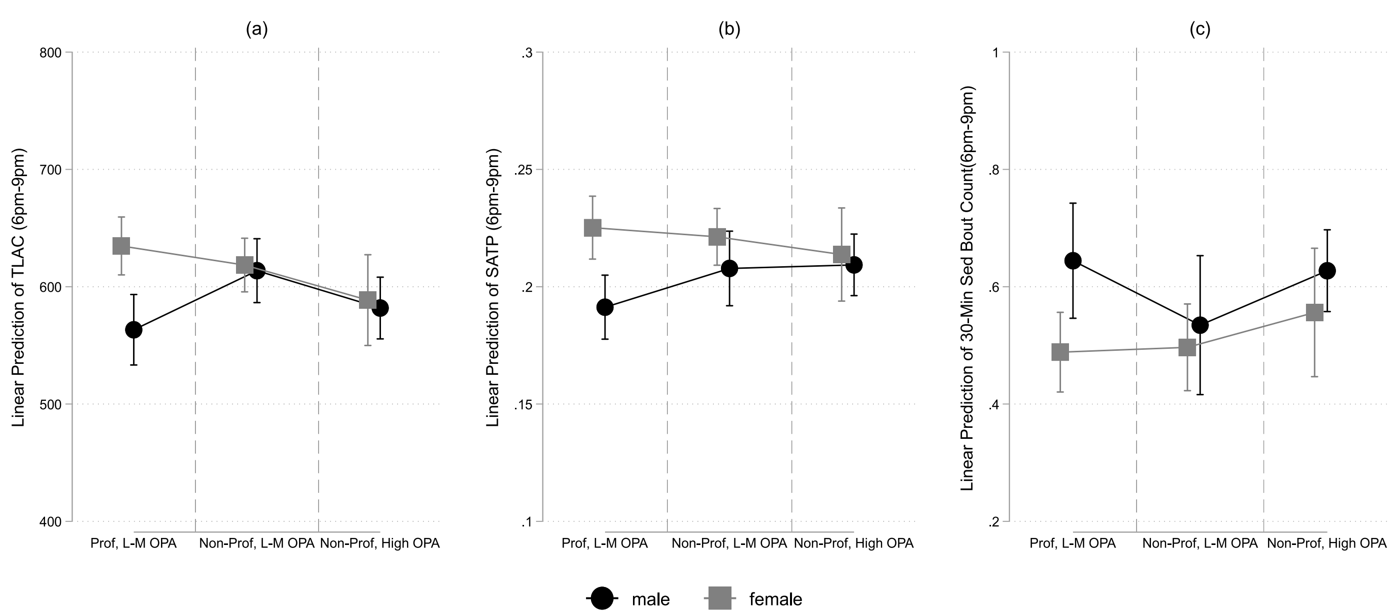

Fig. 1. Predictive margins of PA measures (6pm–9pm) with 95% confidence intervals by gender and occupational group.

3.3. Analytic plan

The analyses proceed in two stages. The first set of analysis examines the gender differences in second-shift summary PA measures in both evening and morning time windows. For the first two outcome measures in the 6pm–9pm window – $TLAC_{6pm\text{-}9pm}$ and $SATP_{6pm\text{-}9pm}$, we estimate generalized estimating equation (GEE) models to account for the clustering of outcome variables within individuals over multiple weekdays, i.e., 2 to 5 eligible weekdays nested within each individual (Liang & Zeger, 1986). We assumed exchangeable correlation among the repeated observations across eligible person-weekdays and used robust standard errors to construct Wald confidence intervals. Correspondent to the proposed hypotheses, three nested GEE linear models were estimated for $TLAC_{6pm\text{-}9pm}$ and $SATP_{6pm\text{-}9pm}$. Model 1 includes the main explanatory variable gender and all control variables. Model 2 adds the variable of occupational group and Model 3 adds interaction terms between gender and occupational group. For the third outcome variable – count of 30-min sedentary bouts, we repeat the same steps using GEE negative binomial models given the overdispersion of this PA outcome. The predictive margins from Model 3 are plotted by gender and occupational group for all the three PA outcome variables (Fig. 1). For the morning time window, we estimate GEE linear models for the PA outcome of $TLAC_{7:30am\text{-}8:30am}$ with the same strategy used for $TLAC_{6pm\text{-}9pm}$. All estimation and inference are obtained using the appropriate NHANES complex survey design. All GEE models are conducted using STATA 16 (StataCorp, 2019).

An additional analysis leverages multilevel function on scalar regression (Goldsmith et al., 2015), which is an extension of function on scalar regression (FoSR) (Reiss et al., 2010) for repeated measures. The FoSR model treats subject-days of minute-level activity (12am–12am) as a function, allowing average LAC across eligible workdays to vary smoothly in the value of covariates (e.g., gender and occupational group). Having multiple days of data results in multilevel functional data, thus the need for multilevel FoSR methods. The multilevel FoSR model estimates covariate-dependent differences in PA at all times of the day in a single model. The use of functional regression in this context has two key merits. First, it can check whether the selected second-shift time windows are reasonable. Second, it allows for evaluation of whether gender differences in PA only manifest in the second-shift hours, or if gender differences persist across the entirety of the day. To be precise, we fitted a varying coefficient model (Hastie & Tibshirani, 1993) with different levels for each covariate of interest. Fixed effects estimation and inference is performed using a fast, local approach (Cui et al., 2022; Sergazinov et al., 2023). Estimation is done using the *mgcv* package (Wood, 2011, 2017) in statistical software R version (4.2.0) (R Core Team, 2022). A more detailed description of model specification is presented in Appendix.

3.4. Sensitivity analysis

We conduct sensitivity analysis by modifying the analytic sample and the observation time window of outcome variables. First, we expand the age ranges from 20 to 49 to 16–65 (n = 829, 3205 person-days) to include all working-age respondents. Second, we focus on a subsample of respondents who are currently partnered (n = 423, 1605 person-weekdays). Third, we use the same set of PA outcomes as for 6:00pm-9:00pm but for a half-an-hour later period 6:30pm-9:30pm to test whether the results are sensitive to time window definitions. The GEE models are re-estimated in these three situations and the results are consistent with what are reported here.

4. Results

4.1. Descriptive patterns

Table 1 shows weighted descriptive statistics of the variables included in the analysis. Men and women are evenly distributed in the analytic sample. Overall, women have higher average $TLAC_{6pm\text{-}9pm}$ and $SATP_{6pm\text{-}9pm}$ than men, and a smaller number of 30-min secondary bouts, indicating women are both more active and engaged in fewer prolonged sedentary behaviors between 6pm and 9pm. For the morning time window, men have higher average $TLAC_{7:30am\text{-}8:30am}$ than women. Approximately half of female respondents are in the "professional, low-to-moderate OPA" group, while a smaller proportion of men (36.11%) are in this group. Men are disproportionately distributed in "non-professional, high OPA group" (46.24%), compared to less than ten percent among women. There is no significant difference in age at examination between men and women. A slightly higher percentage of women (41.85%) have a college degree than their male counterparts (33.60%). Women have higher family income to poverty ratio than men. In terms of family-related characteristics, a lower percentage of women (66.51%) are currently married or cohabiting than men (72.58%); and women also have relatively smaller family size than men in the analytic sample. There is no gender difference in wear time in either the morning or evening time window.

Table 1
Descriptive statistics of analytic sample (n = 614).

	Total (n = 614)	Male (n = 306)	Female (n = 308)	p-value
$TLAC_{6pm\text{-}9pm}$	599.70 (173.18)	576.44 (178.02)	622.84 (166.14)	0.012
$SATP_{6pm\text{-}9pm}$	0.21 (0.09)	0.20 (0.09)	0.22 (0.09)	0.025
Count of 30-min sedentary bouts (6pm–9pm)	0.57 (0.60)	0.62 (0.62)	0.52 (0.58)	0.051
$TLAC_{7:30am\text{-}8:30am}$	187.56 (90.35)	199.43 (94.56)	175.75 (84.88)	0.005
Occupational group				
Professional, low-to-moderate OPA	42.89	36.11	49.65	<0.001
Non-professional, low-to-moderate OPA	29.46	17.65	41.20	
Non-professional, high OPA	27.65	46.24	9.15	
Race				
White	70.75	69.43	72.05	0.011
Black	10.39	8.35	12.42	
Hispanic	14.39	19.23	9.57	
Other	4.47	2.98	5.95	
Age at examination	36.61 (6.59)	36.72 (6.70)	36.50 (6.48)	0.765
College-educated	37.79	33.60	41.85	0.072
Family income-to-poverty ratio	3.46 (1.18)	3.32 (1.21)	3.62 (1.14)	0.032
Married/cohabiting	69.54	72.58	66.51	0.262
Family size	3.10 (1.19)	3.28 (1.26)	2.92 (1.10)	0.032
Wear time (6pm–9pm)	175.04 (10.29)	175.21 (10.05)	174.86 (10.52)	0.652
Wear time (7:30am-8:30am)	47.22 (17.92)	48.16 (17.45)	46.28 (18.35)	0.294

Note: Data are presented as mean (SD) for continuous measures, and % for categorical measures. Two-year examination weight is adjusted for the descriptive statistics.

4.2. Second-shift PA in the 6pm–9pm time window

The results of GEE models predicting the 3 s-shift PA summary measures for the 6pm-to-9pm time window are presented in Table 2. Hypothesis 1 suggests an overall gender difference in the 3 s-shift PA measures. The Model 1 results provide supportive evidence to this hypothesis. Holding all the control variables constant, women have higher $TLAC_{6pm\text{-}9pm}$ ($\beta = 39.06$, $p < 0.01$) than men; and they had greater $SATP_{6pm\text{-}9pm}$ ($\beta = 0.02$, $p < 0.01$), which infer more fragmentation in the accumulation of sedentary behaviors. In line with these results, women have lower incidence rate of 30-min sedentary bouts in the three evening hours (IRR = 0.83, $p < 0.01$) than men. When controlling for

Table 2
Results of GEE models predicting second-shift PA measures during 6pm-to-9pm time window (n = 2338).

	Model 1	Model 2	Model 3
	$TLAC_{6pm\text{-}9pm}$		
Female	39.06** (12.13)	33.70** (12.56)	71.44*** (19.99)
Professional, low-to-moderate (Reference)			
Non-professional, low-to-moderate OPA		1.58 (14.73)	44.10* (21.59)
Non-professional, high OPA		-15.84 (17.18)	10.32 (21.41)
Female: Non-professional, low-to-moderate OPA			-66.64* (27.19)
Female: Non-professional, high OPA			-64.67* (31.05)
	$SATP_{6pm\text{-}9pm}$		
Female	0.02** (0.01)	0.02** (0.01)	0.03*** (0.01)
Professional, low-to-moderate (Reference)			
Non-professional, low-to-moderate OPA		-0.00 (0.01)	0.01 (0.01)
Non-professional, high OPA		-0.00 (0.01)	0.01 (0.01)
Female: Non-professional, low-to-moderate OPA			-0.02 (0.01)
Female: Non-professional, high OPA			-0.03+ (0.02)
	Count of 30-min $Bout_{6pm\text{-}9pm}$		
Female	0.83** (0.05)	0.84** (0.06)	0.76** (0.08)
Professional, low-to-moderate (Reference)			
Non-professional, low-to-moderate OPA		0.97 (0.09)	0.85 (0.12)
Non-professional, high OPA		1.01 (0.10)	0.95 (0.10)
Female: Non-professional, low-to-moderate OPA			1.23 (0.22)
Female: Non-professional, high OPA			1.17 (0.18)

Note: Standard errors in parentheses; + p<0.10, *p<0.05, **p<0.01, ***p<0.001.
Incidence Rate Ratio (IRR) are shown for models estimating gender difference in count of 30-min sedentary bouts. Model 1 controls for all three sets of covariates, Model 2 added occupational group, and Model 3 added gender and occupation interaction term.

occupational group in Model 2, these gender differences in evening second-shift PA measures remain largely the same in the magnitude and statistical significance.

Hypothesis 2 contends that the gender difference in second-shift PA is moderated by occupation group. Model 3 include the interaction term between gender and occupation group. To ease the interpretation, Fig. 1 shows gender gaps in the 3 s-shift PA measures across different occupational groups by plotting predictive margins with 95% confidence intervals for men (in black) and women (in gray) and we report the average marginal gender (being female) effect on each PA measure by occupational group. In accordance with Hypothesis 2, the gender difference in $TLAC_{6pm\text{-}9pm}$ is most pronounced for the "professional, low-to-moderate" group ($\Delta = 66.56$, $p < 0.001$). By contrast, the gender effects are non-significant for the two non-professional occupational groups ($\Delta = -2.95$, $p = 0.87$; $\Delta = -3.35$, $p = 0.89$). Similar patterns are observed for gender difference in $SATP_{6pm\text{-}9pm}$. Women in professional, low-to-moderate OPA group have significantly higher $SATP_{6pm\text{-}9pm}$ than their male counterparts ($\Delta = 0.03$, $p < 0.01$), while the gender differences are absent for the two non-professional groups ($\Delta = 0.01$, $p = 0.39$; $\Delta = -0.001$, $p = 0.92$). The same pattern is found for the count of 30-min sedentary bouts.

4.3. Second-shift PA in the 7:30am-8:30am time window

Table 3 shows the results of GEE models predicting the TLAC in the one morning hour (7:30am-8:30am). In the baseline model, women have less $TLAC_{7:30am\text{-}8:30am}$ than men ($\Delta = -18.82$, $p<0.001$), however, after controlling for occupational group in Model 2, the gender difference in $TLAC_{7:30am\text{-}8:30am}$ is no longer statistically significant. The inclusion of interaction term between gender and occupational group shows that the gender gaps in $TLAC_{7:30am\text{-}8:30am}$ differ across occupational groups. In the professional, low-to-moderate OPA group, women are more active than men in the morning ($\Delta = 16.70$, $p < 0.05$), which is consistent with the pattern of $TLAC_{6pm\text{-}9pm}$. There is no gender difference in $TLAC_{7:30am\text{-}8:30am}$ among workers in the non-professional, low-to-moderate OPA group ($\Delta = -10.80$, $p = 0.20$). Men in the non-professional, high OPA group have higher PA than their female counterparts ($\Delta = -39.80$, $p<0.001$).

4.4. Gender differences in PA in a whole-day view

Fig. 2 shows the results of the multilevel FoSR model. A yellow horizontal line at zero corresponds to no estimated gender difference in PA at the specified minutes. Values above (below) zero indicate that women are more (or less) active than men at that time of day. The FoSR model yields similar patterns identified in the analysis of $TLAC_{6pm\text{-}9pm}$ and $TLAC_{7:30am\text{-}8:30am}$. The gender difference in second-shift PA (LAC) only exists in the "professional, low-to-moderate OPA" group, with confidence interval band entirely above the zero line during 6pm to 9pm. By contrast, the confidence interval bands for the point estimate of LAC contain zero (no gender difference) during the evening second-shift time window for the two non-professional groups. The diurnal patterns support the choice of 6pm–9pm as the primary observation window.

5. Discussion and conclusion

The study presents one of the first pieces of evidence for gender difference in second-shift PA contingent on the first shift, among full-time workers with a regular daytime schedule in a nationally representative sample. Using objective PA measures from accelerometry data, we estimate gender difference in PA volume and sedentary behaviors during second-shift time windows as well as diurnal patterns of minute-level PA. Our conceptual emphasis on the gendered organization of work and family extends PA accumulation from leisure and occupation domains to the household domain. By conditioning the gender difference in second-shift PA on workers' occupations, we identify gender patterns that cannot be reduced to gender inequality in domestic domain.

We find a general gender difference in second-shift PA (6pm–9pm) controlling for other relevant covariates, which supports the second shift thesis that women are expected to accumulate a higher amount of PA from household activities than men (Hypothesis 1). Using objective accelerometry data, our finding is also consistent with existing evidence

Table 3
Results of GEE models predicting $TLAC_{7:30am\text{-}8:30am}$ (n = 2338).

	Model 1	Model 2	Model 3
Female	-18.82*** (4.65)	-8.30 (5.27)	16.70* (7.22)
Non-professional, low-to-moderate OPA		4.18 (5.71)	19.99* (9.79)
Non-professional, high OPA		37.02*** (7.23)	57.58*** (8.43)
Female: Non-professional, low-to-moderate OPA			-27.51* (10.95)
Female: Non-professional, low-to-moderate OPA			-56.50*** (12.83)

Standard errors in parentheses.
+ p<0.10, *p<0.05, **p<0.01, ***p<0.001.

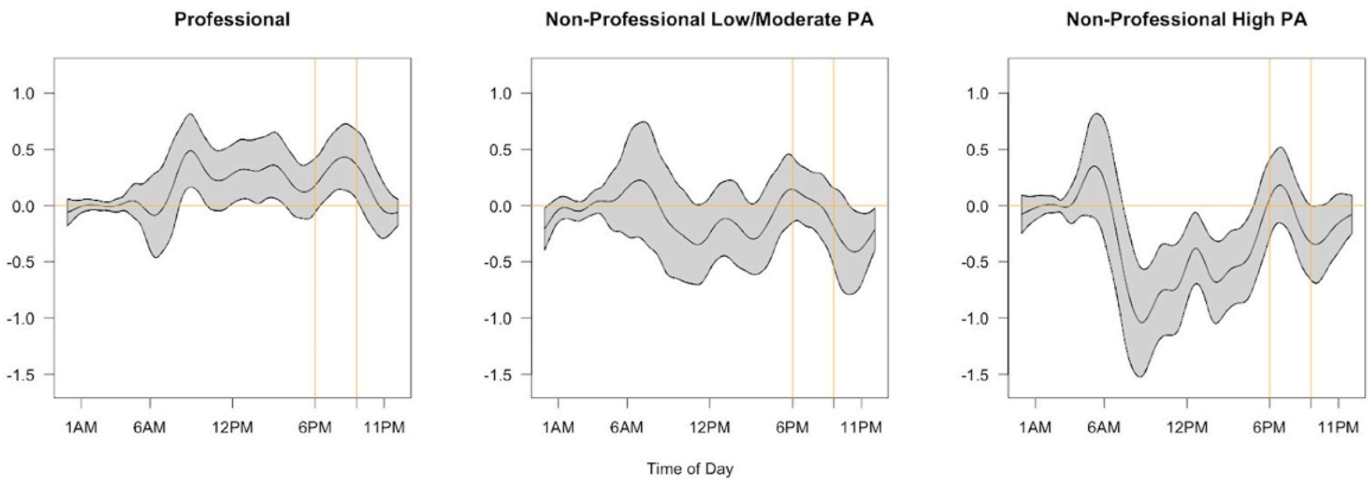

Fig. 2. Point estimates and pointwise 95% confidence intervals for the estimated gender differences by occupational group.

from self-reported data showing that women are more active than men in terms of PA generated by housework and caregiving (Cusatis & Garbarski, 2019; Saffer et al., 2013; Smith et al., 2014). In addition to the gender pattern in the total volume of PA, the second shift is an important context for discerning the gender gap in sedentary behaviors. We identify an overall gender difference in the sedentary behavior among full-time workers that men are more likely to spend their evening hours in prolonged sedentary bouts and less likely to transition out of such state. As the sedentary behavior is increasingly recognized as a risk factor independent of physical activity, breaking sedentary bout at home becomes a complementary strategy to increasing discretionary leisure-time PA (Owen et al., 2009).

Our findings underscore how the organization of work, indicated by the occupational groups, shapes the opportunities of PA accumulation between professional and non-professional workers in gendered ways. When we condition the gender effect by occupational group, the gender gap in second-shift PA is only present for workers in professional occupations on weekdays (Hypothesis 2). The higher second-shift PA among professional women is also confirmed in the 1-h morning analysis, which suggests that professional workers are unlikely to redistribute second-shift tasks across time windows outside of working hours. Consistent with previous work on occupation-specific structural constraints to differential gender division of domestic labor (Usdansky, 2011), we find that, only professional women have greater housework-based PA than their male counterparts. Rooted in the glass-ceiling effect, women are less capable than men to negotiate family obligations especially with the presence of young children. In addition, the notion of intensive mothering of middle-class families may also shed light to our finding and explain why professional women accumulate higher second-shift PA than their male counterparts (Ennis, 2014).

By contrast, men and women in non-professional occupations accumulate similar amount of second-shift PA during the evening hours. Workers in non-professional, low-to-moderate OPA groups show no gender difference in PA volume in either second-shift time window. The same is supported by the results of the functional data analysis, with no statistically significant difference in minute-level PA between non-professional men and women throughout the second-shift time window in the evening. As such, second shift is a more gender-neutral context for PA accumulation for non-professional workers who tend to share unpaid work more equally to address work-family conflict driven by inflexible schedules and lower income (Clawson & Gerstel, 2014; Usdansky, 2011).

Besides counting accumulated amount of PA, we explore the differences in accumulation patterns of second-shift PA via fragmentation of sedentary behaviors and count of 30-min sedentary bouts. In addition to higher PA volume, professional women also accumulate second-shift PA in a more fragmented manner indicated by more frequent transitions between sedentary and active states. This pattern lends evidence to the existing findings on the gendered experience of free time with an objective measure of PA. That is, women's free time – time not associated with paid/unpaid work and personal care, is more likely to be fragmented into short episodes while men spent free time as continuous bouts (Mattingly & Bianchi, 2003). We find that professional men tend to spend their evening time in prolonged sedentary bout. Since we exclude those who usually work over 50 h per week, the observed sedentary bouts are likely to be spent in sedentary leisure rather than work from home. Previous time use study also reveals that men have more free time than women (Sturm, 2019). In this regard, the physical inactivity for professional men may not be attributable to time scarcity. Such sedentary time then affords much potential to increase PA for men in professional occupations.

Although being physically active and avoiding prolonged sedentary bouts are associated with better health outcomes, we contend that the source of PA is an important qualifier for understanding the PA-health association. Previous studies on occupational PA suggest that physically strenuous occupations do not necessarily have health benefits, perhaps because of lower worker control and the lack of adequate time for recovery (Holtermann et al., 2018). In a similar vein, having higher second-shift PA may also be detrimental to health. For instance, taking disproportionately greater share of housework is associated with women's higher psychological distress (Bird, 1999). A recent review shows that employed women's mental health is more adversely affected by housework than men (Ervin et al., 2022). Mothers have higher probability of multitasking at home than fathers in dual-earner families (e.g., doing multiple housework at the same time), which is predictive of worse well-being outcomes such as stress (Offer & Schneider, 2011). Because of these complications, second-shift PA cannot be conceptualized as a health-promoting behavior when isolated from its context. Although doing housework contributes to achieving the recommended level of PA (Lawlor et al., 2002; Murphy et al., 2013), increasing PA level through housework alone may not confer the expected health benefits for women who already work a heavier second shift than men do. Future studies are needed to determine whether second-shift PA has comparable health benefits to leisure-time PA while considering gender differences in both first and second shifts.

We note several limitations in our study. First, although we use theoretical and empirical criteria to define the second-shift time windows for our selected sample, we lack the information on the types of activities the respondents undertook during non-working hours. As a result, we still have a moderate uncertainty of the extent to which the observed light-to-moderate PA can be contributed by second-shift tasks. To obtain a more precise measurement of second-shift PA, future studies may combine accelerometry data with ecological momentary assessment methods to attain necessary information on activity, timing, and setting. Second, collecting data from wearable devices is subject to compliance issues. That is, participants may not consistently wear the PA monitor in accordance with study protocol. Consistent with previous analyses of wearable accelerometers, we attempted to address this problem based on estimated wear time during the time periods of interest, leading to an analytic sample of highly compliant individuals. Given that recent waves do not collect information on work schedules and thus making it impossible to consider the social timetable for the study of PA, we strongly recommend future NHANES data collection resumes the 2005-06 questions about work schedules. In addition, although we have included family characteristics necessary to understand the demand of second-shift tasks, we wish to have information on which housework is delegated to commercial means, care workers, and unpaid family helpers. Finally, the public-use NHANES data does not release household rosters that facilitate the identification of married or cohabiting partners, or single parents with children. We opt to use public-use NHANES for a wide research community in this study of gender gaps of workers comparable in the large set of covariates at the expense of the PA of identified partner.

Overall, the present study provides novel evidence to the gender difference in PA using accelerometer-based measures among full-time workers in a nationally representative sample. By focusing on the second-shift time windows, we identify gender difference in PA and sedentary behaviors that might be contingent on occupational-specific structural constraints. Contextualizing gender difference in PA informs the barriers and potential opportunities of increasing PA beyond promoting leisure-time activities. Our findings also suggest future research to examine PA-health link in social context to identify solutions for groups with differential circumstances and needs.

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Ethical statement

All individual-level data used in the research article is secondary data and publicly available, which is collected by CDC National Center for Health Statistics.

CRediT authorship contribution statement

Wenxuan Huang: Conceptualization, Methodology, Formal analysis, Visualization, data interpretation, Writing – original draft, Writing – review & editing. **Lingxin Hao:** Conceptualization, Methodology, data interpretation, Writing – original draft, Writing – review & editing, Funding acquisition, Supervision. **Xingyun Wu:** Conceptualization, data interpretation, Validation, Writing – review & editing. **Xiao Yu:** Conceptualization, data interpretation, critical feedback, Writing – review & editing. **Erjia Cui:** Data interpretation, Methodology, Writing – review & editing, critical feedback. **Andrew Leroux:** Conceptualization, Formal analysis, Visualization, data interpretation, Software, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

Appendix

Table A1
Constructed Occupational Group and Detailed Occupational Categories

	Professional	Non-Professional
Low-to-moderate OPA	•Management •Business, financial operation •Computer, mathematical •Architecture, engineering •Life, physical, social science •Community, social service •Legal •Education, training, library •Arts, design, entertainment, media •Healthcare practitioner, technical	•Healthcare support •Sales and related •Office administrative
High OPA	n/a ***no professional occupations have high PA during work	•Protective service •Food preparation, serving •Building, grounds clean, maintenance •Personal care, service •Farming, fishing, forestry •Construction, extraction •Installation, maintenance, repair •Production •Transportation, material moving

Table A2
Sociodemographic Characteristics of Analytic Sample (n = 614) and Sample without Applying Wear Time Restrictions (n = 920)

	Reported analytic sample (n = 614)	Not selecting wear time (n = 920)
Female	50.13	47.51
Occupational group		
Professional, low-to-moderate OPA	42.89	38.93
Non-professional, low-to-moderate OPA	29.46	26.87
Non-professional, high OPA	27.65	34.19
Race		
White	70.75	69.40
Black	10.39	10.87
Hispanic	14.39	15.44
Other	4.47	4.29
Age at examination	36.61 (6.59)	36.27 (6.84)
College-educated	37.79	35.30
Family income-to-poverty ratio	3.47 (1.18)	3.41 (1.23)
Married/cohabiting	69.54	69.63
Family size	3.10 (1.19)	3.09 (1.27)

Note: Data are presented as mean (SD) for continuous measures, and % for categorical measures. Two-year examination weight is adjusted for the descriptive statistics.

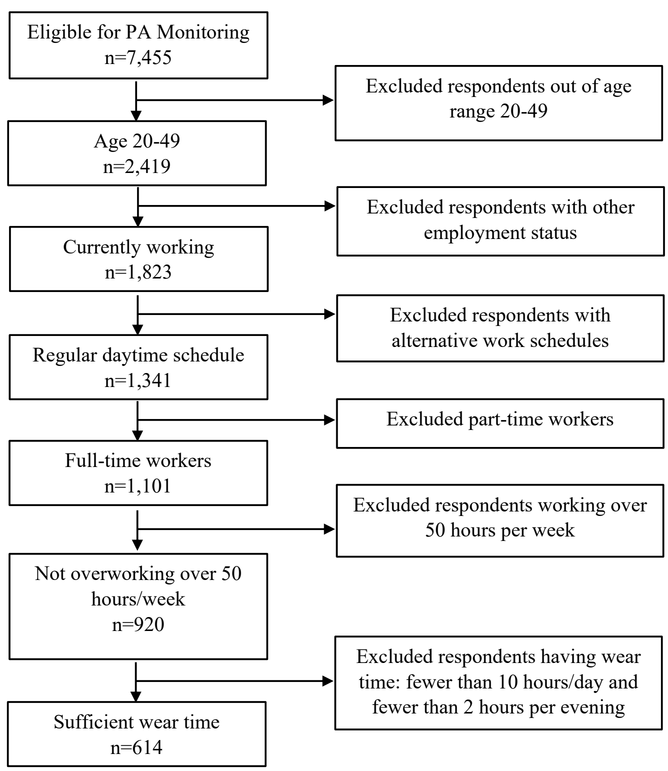

Fig. A1. Sample Selection Flowchart. .

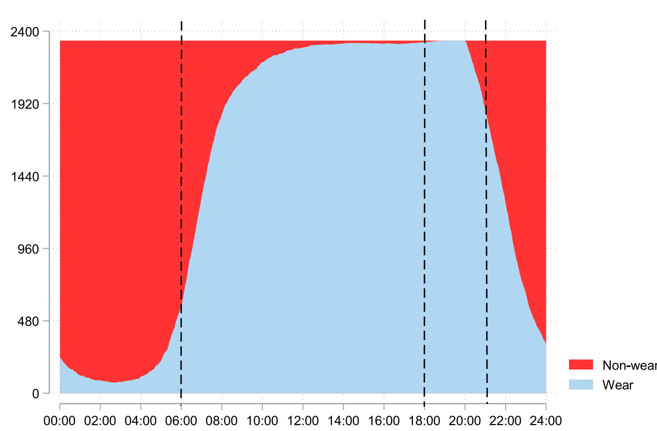

Fig. A2. Distribution of Wear and Non-Wear Status over 24-Hour Period of Analytic Sample. .

The Function on Scalar Regression Model

Model Setup

The function on scalar regression (FoSR) model estimated in the manuscript assumes a generative data model of

$$y_{ij}(t) = \beta_0(t) + \sum_{p=1}^{p} f_p(t)X_{ip} + \beta_1(t)Female_i + \beta_2(t)NP_i^{LPA} + \beta_3(t)NP_i^{HPA} + \beta_4(t)Female_i \times NP_i^{LPA} + \beta_5(t)Female_i \times NP_i^{HPA} + b_i(t) + v_{ij}(t) + \varepsilon_{ij}(t)$$

where $i = 1, \ldots, N$ denotes subject, $j = 1, \ldots J_i$ denotes day (participants can have varying numbers of valid days, hence J_i), and $t = 1, \ldots, 1440$ corresponds to minute of the day. The outcome, $y_{it}(t)$ is the observed minute level log-transformed activity count for subject i on day j at minute t. The fixed effects component of the model (all terms except for $b_i(t) + v_{ij}(t) + \varepsilon_{ij}(t)$) are modelled as varying coefficients. That is, each covariate is allowed to have a time-specific effect on average activity level. Here, X_{ip} represent covariates which are not of our primary interest. They include white race indicator, age at accelerometer wear, family poverty to income ratio, marital status, and college education. The remaining variables in the model, $Female_i$, NP_i^{LPA}, and NP_i^{HPA} correspond to indicators for female gender, non-professional low-to-moderate intensity PA occupation, and non-professional high intensity PA occupation, respectively.

The fixed effects, $\beta_k(t), f_p(t)$ for $p = 1, \ldots, P$ and $k = 1, \ldots, 5$ are modelled flexibly using penalized regression splines. That is, we express each coefficient function as a sum of a relatively large number of basis functions, penalizing the curvature of the estimated function to balance the tradeoff between goodness of fit and model overfit. Here, each coefficient function is modelled using cyclic cubic regression splines with dimension 20.

Since the data tend to be correlated within days and across days within subjects, we need to model this correlation to obtain accurate standard errors on model parameters. This is done through the inclusion of subject- and subject-day- specific random functional intercepts, $b_i(t)$ and $v_{ij}(t)$, respectively. These random functional intercepts are assumed to be Gaussian processes.

In the model, $\varepsilon_{ij}(t)$ represents the independent and identically distributed residual term in the model which are unexplained by the fixed and random components of the model.

Additional assumptions

The FoSR model here assumes that the subject- $b_{ij}(t)$) and subject-day ($v_{ij}(t)$ specific random effects are mutually independent of each other and the residuals ($\varepsilon_{ij}(t)$).

Estimation

Estimation is performed following the fast univariate inference approach of Cui et al. (2022). Here, inference is performed using 2000 bootstrap replicates of the data. Each of the pointwise coefficient estimates are smoothed using dimension 20 penalized cubic regression spline basis with REML smoothing parameter selection via the *mgcv* package. Pointwise 95% confidence intervals are constructed using$\pm Z_{0.975}$ times the standard error of the quantities of interest across the smoothed bootstrap estimates. Note that we construct the contrasts $\widehat{\beta}_1(t)$, $\widehat{\beta}_1(t) + \widehat{\beta}_4(t)$ $\widehat{\beta}_1(t) + \widehat{\beta}_5(t)$ to obtain the estimated gender differences in the professional, non-professional low-to-moderate OPA, and non-professional high OPA groups.

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