Article

Constrained choices: Combined influences of work, social circumstances, and social location on time-dependent health behaviors

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ABSTRACT

Background: Physical activity and sleep are two time-dependent behaviors with important health implications. The amount of time people have to engage in these behaviors may vary based on their everyday work, social circumstances (e.g., parenthood), and social location (e.g., gender).

Aims: The current study aimed to explore the ways work, social circumstances, and social locations combine that lead to heterogeneity in the time-dependent health behaviors of physical activity and time spent in bed (i.e., sleep) among a young adult population. We drew upon two conceptual frameworks—Constrained Choices and an intersectionality perspective—and examined multiple work characteristics (e.g., number of jobs), social circumstances (e.g., household income), and social locations (e.g., U.S. nativity) relevant to young adulthood.

Methods: 2015–2016 data from a Minneapolis-St. Paul, U.S. cohort of 1830 young adults (25–36 years) were analyzed using conditional inference tree (CIT)—a data-driven approach which identifies population sub-groups that differ in their outcome values as well as in the interacting factors that predict outcome differences. Sensitivity analyses to evaluate CIT robustness were also performed.

Results: CITs revealed four relevant sub-groups for physical activity (sub-group averages ranged = 2.9–4.9 h per week), with working mothers achieving the least activity, and six relevant sub-groups for time in bed (range = 7.8–8.7 h per day), with full-time working men obtaining the least. In both models, parent status and employment status/hours were found to consistently differentiate behavior among women but not men.

Conclusion: According to these data, time to engage in physical activity and time in bed was constrained by particular everyday contexts (work and parent status) and the extent to which these contexts mattered also depended on gender. If replicated in other studies, results suggest equitable strategies are necessary to assist all parents and workers in engaging in these time-dependent health behaviors for long-term health.

Introduction

Physical activity and sleep are important health behaviors that require a dedicated time commitment. Both limited physical activity and inadequate sleep have been associated with a heightened risk for many chronic conditions, including diabetes, hypertension, and cardiovascular disease, as well as mortality (Itani, Jike, Watanabe, & Kaneita, 2017; Kraus et al., 2019; Warburton & Bredin, 2017). While other health behaviors, such as an unhealthy diet, can lead to similar conditions, physical activity and sleep are health promoting behaviors first and

foremost dependent on time. In fact, recommendations for both behaviors are specified in time-based ways (i.e., sleep 8 h per day; exercise 150 min per week) (Health & Services, 2018; Panel, 2015), and research suggests not all persons achieve the minimum guidelines (Zenko, Willis, & White, 2019; Liu, 2016).

Underscoring the time-dependency of physical activity and sleep illuminates the deterministic role time plays in these health behaviors (Strazdins et al., 2011). While all people have an equal distribution of time (i.e., 24 h a day), the demands on, value of, and capacity to control it varies across social groups and results in time constraints or

protections for health and health behavior (Venn & Strazdins, 2017). For example, gender norms persist in such a way that daily time commitments continue to disproportionately affect women; even among U.S. full-time workers, women spend more daily time on household and family responsibilities while men have more time available for leisure (BLS, 2019a). In addition, people of color compared to white people experience time disadvantages doing ordinary activities (e.g., increased time required for cars to yield to pedestrians or identify a health provider accepting patients), and some of this disadvantage can be attributed to structural racism and discrimination (Gee, Hing, Mohammed, Tabor, & Williams, 2019; Goddard, Kahn, & Adkins, 2015; Kugelmass, 2016). Despite its fundamental role, scholars have previously critiqued how time as well as its social patterning remain under-integrated into the research and action aiming to improve health behavior (Gee et al., 2019; Venn & Strazdins, 2017).

In addition to time variation by social position, time demands and control may fluctuate developmentally and may be especially salient during the transition from early to middle adulthood. The large majority of U.S. young adults are workers in the labor force (BLS, 2019b), spending on average one-third of their day on work-related activities (BLS, 2017). Young adulthood is also the most common developmental period for individuals to enter into partnerships, have children, and/or finish postsecondary education and training (Bureau, 2018; Hamilton, Martin, Osterman, & Rossen, 2019; Statistics, 2019). Navigating the competing demands and transitions has the potential to influence the day-to-day ability to prioritize time-dependent behaviors, which could have lasting implications for behavioral patterning and health over the life course (Nelson, Story, Larson, Neumark-Sztainer, & Lytle, 2008). Prior research supports that each of these work and social circumstances common to young adulthood may affect health and health behavior (Berge, Larson, Bauer, & Neumark-Sztainer, 2011; Miller et al., 2019; Winkler, Mason, Laska, Christoph, & Neumark-Sztainer, 2018). What has been less examined is the ways that these everyday realities (1) are experienced in combination and (2) operate within socialized hierarchies and systems.

We draw on two conceptual frameworks to inform our exploration of the ways work, social circumstances, and social hierarchies combine to differentially shape time-dependent health behaviors in young adulthood. The first, Constrained Choices (Bird & Rieker, 2008; Rieker & Read, 2017), asserts that an individual's "choice" (i.e., agency and options) to engage in health behaviors is fundamentally shaped by decisions and actions occurring across multi-level contexts—work, family, community, public policy—which can either impose barriers or enhance opportunities for individuals and groups to prioritize health. In regards to time, actions and decisions at these multiple levels as well as their interactions may produce an uneven distribution of barriers and supports on the resource of time resulting in differential outcomes for activity and sleep. The second framework—an intersectional approach (Bowleg, 2012)—highlights that social categories measured at the individual-level (e.g., race/ethnicity, gender) are importantly reflections of systems of privilege and oppression at the socio-structural-level (e.g., racism, sexism); such social locations are not experienced as independent exposures but rather concurrent, intersecting realities.

In this study, we use each framework to inform our research aim, constructs, and approach. We focus on the Constrained Choices' family and work context to inform the everyday work and social circumstances that may be relevant to people's ability to find time for physical activity and sleep. Work and social roles create daily routines and carry expectations, which create different advantages, limitations, and even stressors on time for health behavior (Rieker & Read, 2017). As such, we selected to consider a variety of work and social circumstances that are not only socially-patterned but may have different effects (negative or positive) on time for behaviors. Using an intersectional perspective, we ensured multiple, interlocking social locations (e.g., race/ethnicity, gender, US nativity) were examined and also extend the idea to work

and social circumstances which may also be simultaneously experienced. Using these elements, we explore the interwoven and interdependent ways that work and social circumstances may uniquely combine with social location to constrain or enhance individuals' time for physical activity and sleep. We assume such combinations at the individual-level will produce differences observable at the population level.

The overall study aim is, therefore, to explore the ways work, social circumstances, and social locations combine that contribute to heterogeneity in the time-dependent health behaviors of physical activity and sleep in a young adult population. We employed a data-driven approach called conditional inference tree (CIT) to identify sub-groups in the population who not only differ in their outcomes, but also on the interacting influences leading to outcome differences. CIT is a recursive partitioning method from a statistical family of methods adopted from machine learning that build upon more traditional approaches (e.g., regression modeling). Traditional statistical approaches often aim to evaluate the independent effects of single predictors, which does not capture the constellation of interacting influences that shape outcomes (Nayak, Hubbard, Sidney, & Syme, 2018). By using CIT, we were able to systematically explore the interactions among influences and understand for which population groups influences are, or are not, relevant without sacrificing important statistical considerations, such as type 1 error. In uncovering which work, social circumstances, and social locations interact, we may be able to better tailor interventions and create more equitable policies to further support people in achieving these beneficial time-dependent health behaviors.

Methods

Study design and population

Data were drawn from Project EAT (Eating and Activity in Teens and Young Adults), a longitudinal study of weight-related health from adolescence through young adulthood. Originally in 1998–1999 (EAT-I), a cross-sectional investigation of 4746 adolescents from 31 public secondary schools in Minneapolis-St. Paul, Minnesota was completed using surveys and anthropometric measurements (Neumark-Sztainer et al., 2002). Given growing interest in weight-related health, a decision was made to follow-up with participants who provided sufficient contact information (n = 3672) at 5-year intervals. The current analytic sample consists of 1830 young adults (range = 25–36 years) who completed the fourth survey in 2015–2016 (EAT-IV). Compared to the original sample, the 2015–2016 sample has a slightly larger proportion of participants who are White, female, and of a higher socioeconomic status. A consent form was provided to participants at the time of the survey, and survey completion implied written consent. The University of Minnesota's Institutional Review Board Human Subjects Committee approved all protocols.

Survey development

The development of all Project EAT surveys was informed by social cognitive theory and an ecological perspective and followed a systematic process, including: theoretical framework development, conducting formative focus groups, pilot testing, refining survey items, and psychometric testing (Larson, Neumark-Sztainer, Story, van den Berg, & Hannan, 2011). A similar process was used for the EAT-IV survey, and a life course perspective (Fine & Kotelchuck, 2010) was further integrated in survey development to capture the various life events (e.g., parenthood) characteristic of young adulthood. The EAT-IV survey was pre-tested by 35 young adults, and test-retest reliability for each item was examined in a subgroup of 103 participants who completed the survey twice within four weeks.

Input variables

We examined 12 input (predictor) variables (see Table 1). The variables represent different social locations, work, and social circumstances that are available for all participants. Variable selection was theoretically-informed using an intersectional perspective and the Constrained Choices framework, and we assumed each had the potential to influence (constrain or enhance) time for physical activity and sleep behavior either through independent or interdependent effects.

Outcomes

The two study outcomes were physical activity, operationalized as weekly hours of moderate-vigorous physical activity (MVPA), and sleep, operationalized as daily hours spent in bed. MVPA was measured with two survey items asking how many hours participants spent in a usual week doing strenuous (e.g., jogging) and moderate (e.g., easy bicycling) exercise (Godin & Shephard, 1985). The six responses for each item ranged from "None" to "6+ hours a week" (test-retest r = 0.84), and were combined to create a continuous scale of total usual hours per week (Haines, Neumark-Sztainer, Wall, & Story, 2007).

Daily hours spent in bed was measured with two items asking participants to report the hour, minutes, and A.M./P.M. for when they "go to bed (to go to sleep)" as well as "get out of bed (to start your day)." Participants reported these for both a typical weekday and weekend day (test-retest r = 0.61–0.86 (Pasch, Laska, Lytle, & Moe, 2010);), which were combined to create a weighted daily average. Prior actigraphic studies among young adults suggests that hours spent in bed may equate to approximately 1 h less of actual sleep time (Youngstedt et al., 2016).

Statistical analysis

We performed descriptive analyses on all variables to examine the prevalence of each social location, work, and social circumstance in the cohort of young adults (Table 2).

Conditional Inference Trees (CITs). We used the recursive partitioning method of conditional inference trees (CITs) (Hothorn, Hornik, & Zeileis, 2006; Strobl, Malley, & Tutz, 2009) to address our aim of exploring the interacting influences (input variables) contributing to differences in weekly MVPA and daily bedtime hours in separate models. CIT is a nonparametric approach that considers all input variables concurrently and then subsequently divides ("partitions") participants on the input variables into discrete sub-groups if the outcome values statistically differ across input variable sub-categories (Strobl et al., 2009). CITs identify these sub-groups through a process of using regression modelling to first identify from all the input variables which has the strongest bivariate association with the outcome; then to detect the best binary cut point to partition the participants (if more than one possible binary split point exists); and, finally to recursively repeat those two steps conditionally within each sub-partition of the sample (including re-evaluating variables already used to split if additional splits exist) until a stop criterion is met. The process results in final distinct participant sub-groups where the relevant input variables for each sub-group can be observed in a graphic display that resembles an inverted "tree" structure. The specific CIT software package (Hothorn & Zeileis, 2015) used in this study applied a conservative approach to building "trees" (i.e., controlled for inflation of overall type 1 error set at P = 0.05 using Bonferroni correction); prevented deletion of participants with missingness on input variables using a surrogate variable; and allowed us to overcome shortcomings of other recursive partitioning approaches, such as bias towards variables with many categories and overfitting (i.e., modelling random versus systematic variation). Please see Hothorn and Zeileis (2015) and Hothorn et al. (2006) for additional information on the CIT approach used.

Sensitivity Analyses. We conducted two sensitivity analyses for the MVPA and daily time spent in bed CITs—one planned a priori and a second based on initial findings.

The planned sensitivity analysis addressed the most important drawback to using CITs, which is their vulnerability to random patterns

Table 1
Description of work, social circumstances, and social location input variables.

Variable	Description
Work Circumstances	
Employment Status & Work Hours	Assessed with two survey items. The first asked participants to select their current work situation (Bauer, Hearst, Escoto, Berge, & Neumark-Sztainer, 2012), such as full-time work and stay-at-home caregiver (test-retest percent agreement = 93%). The second item, which was asked only among working participants, asked about the number of weekly hours they currently work for pay (test-retest correlation = 0.80). We combined the responses to create 5 categorizations of employment status and usual weekly hours worked following the U.S. Internal Revenue Service definition of full-time work ($\geq$ 30 h per week(IRS, 2017)): Long full-time (reports full-time work and >40 h per week), Regular full-time (reports full-time work and 30–40 h per week), Part-time (reports part-time work), Caregivers (reports stay at home caregiver or not currently working for pay), and Unemployed.
Number of jobs	To assess the number of jobs a participant may need to juggle, we used an item that asked working participants to report the number of jobs they worked for pay outside of their home (response range = '0' to '4 or more' jobs; test-retest correlation = 0.66). Using these item responses and information from participants' current work situation, we created the following 3 categories: No job (assigned to those reporting a Caregiver or Unemployed employment status), 1 job (assigned to those reporting 1 job or those reporting long full-time, regular full-time, or part-time work and no job outside the home), and 2 or more jobs (assigned to those reporting at least 2 jobs).
Social Circumstances	
Parent status	Reports having at least one child (test-retest correlations for number of children = 0.98) living in their home $\geq$ 50%
Partner status	Reports having a romantic significant other (test-retest percent agreement = 98%) and currently living with significant other (test-retest percent agreement = 97%)
Student status (current)	Assessed with an item asking participants to best describe their student status for the majority of the previous year (test-retest percent agreement = 95%) to capture time- and social related aspects of current study. To resolve small cell sizes, responses were categorized into: Not a student; Part-time student at a four-year, community, or technical college; Full-time student at a four-year, community, or technical college; and Graduate student (the graduate response did not differentiate full- versus part-time status).
Household Income	Participants reported their total household income before taxes in the past year and selected from 6 response options: < $20,000, $20,000-$34,999, $35,000-$49,999, $50,000-$74,999, $75,000-$99,999, and $100,000 or more (test-retest correlation = 0.94).
Perceived difficulty living on income	Measured with an adapted item asking the degree of difficulty participants currently experience living on their total household income (Price, Choi, & Vinokur, 2002). Participants selected from 4 response options: Not at all difficult, Somewhat difficult, Very difficult or can barely get by, Extremely difficult or impossible (test-retest correlation = 0.83).
Social Locations	
Gender	Based on reports at EAT-I to two response options: Male or Female
Race/Ethnicity	Race/ethnicity was based on reports at EAT-I and responses were grouped into 5 categories: White, Black or African American, Hispanic, Asian/Asian-American, and Native Hawaiian/Pacific Islander or American Indian/Alaska Native or Two or more Races (this last category combined 3 responses to resolve small cell sizes).
US Nativity status	U.S. nativity was based on reports at EAT-I as either being born in the U.S. or outside the U.S.

(continued on next page)

Table 1 (*continued*)

Variable	Description
Educational Attainment	Educational attainment was conceptualized as a crude marker of social class and was measured with the item asking the highest level of education completed (test-retest percent agreement = 97%). Responses were categorized to resolve small cell sizes into: High School degree/GED or less, Vocational/technical program or Associate degree, Bachelor degree, and Graduate/Professional degree.
Age	Age was dichotomized into 2 groups at the median: 25–31 years and 32–36 years.

Table 2

Input and Outcome Variables in Young Adult Sample (n = 1830).

		n (%)	Mean (SD)
Work Circumstances			
Employment status & Hours			
	Long Full-time	613 (34)	
	Regular Full-time	753 (42)	
	Part-time	191 (11)	
	Caregivers	162 (9)	
	Unemployed	61 (3)	
Number of Jobs			
	No Job	223 (13)	
	1 Job	1313 (74)	
	2 or More Jobs	230 (13)	
Social Circumstances			
Parent- % yes		822 (45)	
Partnered- % yes		1269 (70)	
Student status (current)			
	Not a student	1559 (85)	
	Part-time	77 (4)	
	Full-time	71 (4)	
	Graduate	120 (7)	
Household Income			
	<$20,000	133 (7)	
	$20,00-$34,999	230 (13)	
	$35,000-$49,999	289 (16)	
	$50,000–74,999	402 (22)	
	$75,000-$99,999	310 (17)	
	≥ $100,000	435 (24)	
Difficulty living on household income			
	Not at all	781 (43)	
	Somewhat	801 (44)	
	Very difficult or can barely get by	187 (10)	
	Extremely difficult or impossible	46 (3)	
Social Location			
Gender- % Female		1042 (57)	
Race/Ethnicity			
	White	1241 (68)	
	Black	154 (9)	
	Hispanic	63 (4)	
	Asian	268 (15)	
	HPI, NA/AI, or Mixed	90 (5)	
Nativity- % U.S. Citizen		1648 (91)	
Educational Attainment			
	H.S. degree or less	415 (23)	
	Vocational/Technical Program or Associate degree	446 (25)	
	Bachelor degree	654 (36)	
	Graduate/Professional degree	305 (17)	
Age- % 32 years old or older		928 (51)	
Time-Dependent Behaviors			
MVPA in a usual week (self-reported)			4.3 (3.7)
Daily time spent in bed (self-reported)			8.1 (1.0)

HPI, Hawaiian or Pacific Islander; NA/AI, Native American or American Indian; Mixed, selecting more than 1 race; MVPA, moderate-vigorous physical activity
Item missingness ranged from 0-<5%.

in the data. The first splitting variable of a CIT drives the shape of the rest of the "tree" and thus the final sub-groups identified; if this decision is based on a non-replicable association, then the conclusions of the individual CIT are unreliable (Strobl et al., 2009). Therefore, we performed a conditional random forest sensitivity analysis to evaluate whether the initial variables of the CITs were due to chance. Conditional random forest aggregates an ensemble of many CITs, and, through computing variable importance scores, provides clarifying evidence whether the initial variables selected in the original CIT are the same as observed across a "forest" of CITs (Strobl et al., 2009). We used the "cforest" ensemble method to perform the analysis, which grew 1000 CITs, used bootstrap sampling, and ensured limited correlation between trees. We then used the overall variable importance scores to descriptively rank each input variable from the most to least robust input variable and examined whether the initial variables of the CIT were the same as those reported for the "forest." For additional information on the computation of importance scores and the conditional random forest methods used, please see Strobl et al. (2009) and Hothorn and Zeileis (2015).

We added a second sensitivity analysis after observing the results from the MVPA and daily bedtime CITs, which suggested some important differences in the interacting influences (input variables) by gender. Specifically, we observed more influences and greater sub-group differentiation among women compared to men, which may have been driven by the unbalanced representation of women in the participant sample (57% women)—a larger sample size enables greater detection of smaller effects leading to greater differentiation. For this analysis, we performed a second CIT for each outcome using a gender balanced sample created by randomly selecting female participants to match the male sample size (n = 788 men and n = 788 women) and set the overall significance threshold to P = 0.10 to increase our sensitivity of detecting differences for both men and women.

We used R 3.5.1 in 2018 using the "partykit" package with "ctree" and "cforest"" to perform the CIT and random forests, respectively (Hothorn & Zeileis, 2015). Descriptive analyses for participant characteristics were performed using in Stata 15.SE (College Station, TX).

Results

Participants

Descriptive data for all work, social circumstances, and social location variables among participants are shown in Table 2.

Moderate-vigorous physical activity (MVPA)

Results from the MVPA CIT (Fig. 1) indicated four final sub-groups differing in MVPA (range = 2.9–4.9 h per week), which were shaped from three of the 12 input variables—gender, parent status, and employment status & hours. Gender demonstrated the strongest association with MVPA (i.e., first splitting variable), which partitioned women from men. No other input variable was relevant for men, resulting in all men comprising one of the final four sub-groups that displayed the highest rate of weekly MVPA (mean = 4.9 h/week, SD = 4.0). The remaining three sub-groups occurred among women, in which interactions with parent status as well as employment status & hours were observed. The least weekly MVPA occurred among working (Long full-time, Regular full-time, Part-time) and unemployed mothers (mean = 2.9 h/week, SD = 3.0); in contrast, both women who were non-parents (mean = 4.5 h/week, SD = 3.6) as well as mothers who were stay-at-home caregivers (mean = 4.4 h/week, SD = 3.8) demonstrated similar and higher MVPA rates.

Sensitivity analyses using the gender-balanced CIT provided additional support for the gender patterns observed in Fig. 1, as a similar pattern of sub-group differentiation among women and not men was observed (data not shown). Results from the conditional random forest
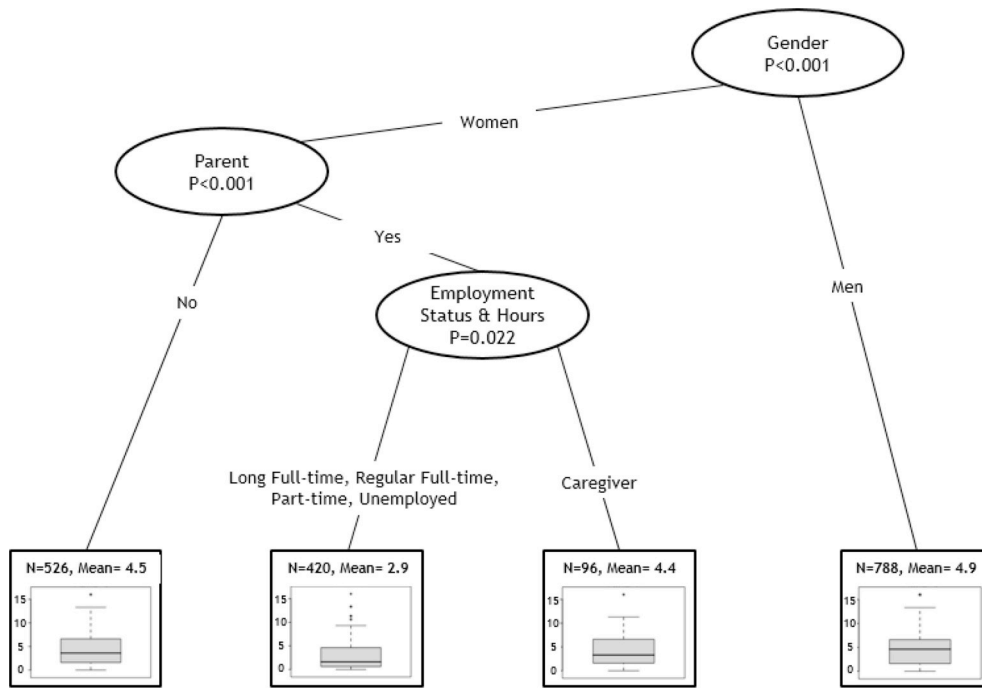
Fig. 1. Conditional inference tree for weekly hours of MVPA (N = 1830).
Note. MVPA, moderate-vigorous physical activity.
Box plot values available in Supplemental Appendix A.

also provided support for the structure and sub-groups in Fig. 1, as the top two input variables identified in Fig. 1, gender and parent status, were also the same as those identified across an aggregate of 1000 CITs (Appendix C).

Daily bedtime hours

Results from the CIT for daily hours spent in bed (Fig. 2) indicated six final sub-groups differing in daily bedtime hours (range = 7.8–8.7 h per day), which were identified from four significant input variables. Employment status & hours demonstrated the strongest association with
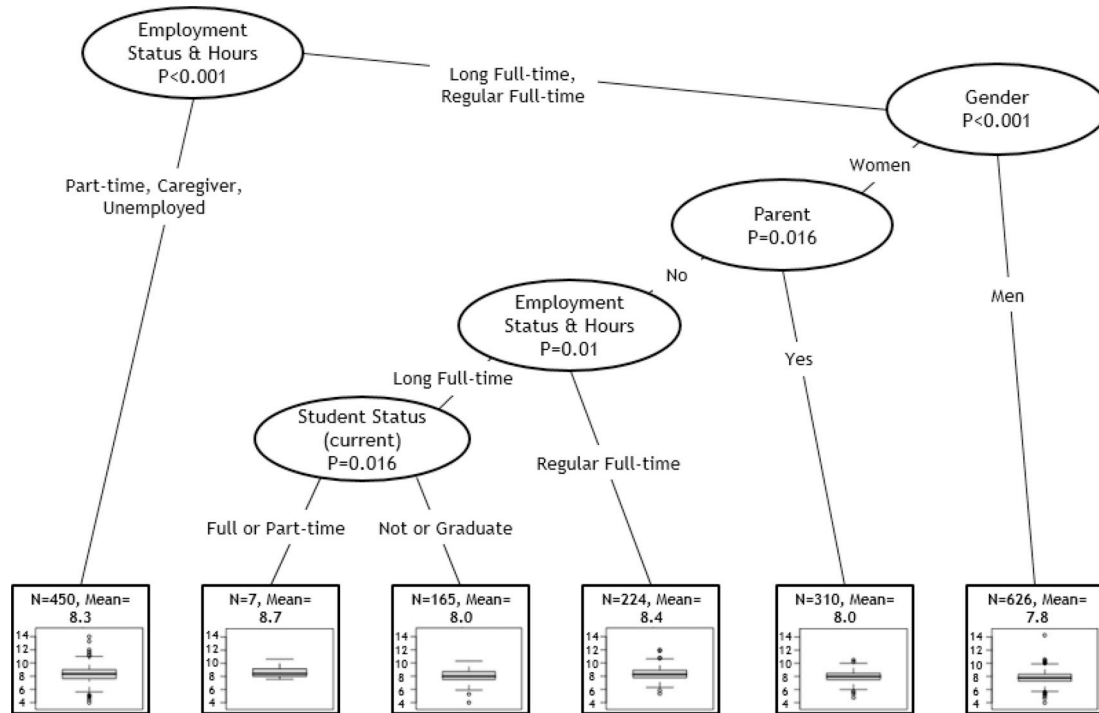

Fig. 2. Conditional inference tree for daily hours spent in bed (N = 1782).
Note. Participants must have outcome data to be included in the CIT. N = 48 participants (2.6% of sample) had missing time in bed data.
Box plot values available in Supplemental Appendix B.

bedtime hours, which first partitioned long and regular full-time workers with less bedtime hours from part-time workers, caregivers, and unemployed participants with more hours. No other input variables were identified as relevant for part-time workers, caregivers, and unemployed participants; however, several input variables differentiated the full-time workers. Among full-time workers, gender demonstrated the strongest association with daily bedtime hours, which partitioned men from women. For full-time working men, no other input variable was relevant, resulting in a final sub-group that displayed the least amount of daily time in bed (mean = 7.8, SD = 0.9). In contrast, several variables were identified to contribute to the heterogeneity among full-time working women, including parent status, employment status & hours, and current student status. Among full-time working women, mothers (mean = 8.0, SD = 0.9) as well as non-mothers who worked long full-time hours and were not currently a full- or part-time student (mean = 8.0, SD = 0.9) demonstrated less time in bed than the other sub-groups.

Sensitivity analyses using the gender-balanced CIT provided additional support for the gender patterns observed among full-time workers, as a similar pattern of input variables only differentiating women and not men was identified (data not shown). Results from the conditional random forest also provided support for the structure and sub-groups identified, as the top two input variables identified in Fig. 2, employment status & hours and gender, were also the same as those identified across an aggregate of 1000 CITs (Supplemental Appendix C).

Discussion

This study aimed to explore the ways work, social circumstances, and social locations combine that lead to population differences among young adults in the time-dependent health behaviors of physical activity and sleep. Using both a theoretically-informed and data-driven approach, we identified several population sub-groups varying in time spent on these health behaviors as well as a pattern for three interacting influences—gender, parent status, and employment status & hours—-which consistently led to differences. Findings support that participants' time to engage in these health behaviors may be constrained by particular everyday contexts (e.g., work and parent status) and that the extent to which these contexts matter further depended on social location (e.g., gender). In particular, both physical activity and time spent in bed were more dependent on a variety of work and social circumstances among women than among men, with working mothers demonstrating a particular vulnerability for limited time. Results also suggest employment status and hours were important influences, highlighting a need for increased attention to the role of work in health behavior research.

Working mothers were the subgroup with the least amount of weekly physical activity—2 hours less than men—as well as having less time in bed than most of the other identified sub-groups of women. Working mothers having less time for health behaviors may be unsurprising, given a public perception that the pressures of multiple social roles are worse for women than men (Shockley, Shen, DeNunzio, Arvan, & Knudsen, 2017). Literature has also documented the independent effects parent status, gender, and work status have on time-dependent health behaviors (Bellows-Riecken & Rhodes, 2008; Hagen, Mirer, Palta, & Peppard, 2013; Virtanen et al., 2009; Zomers et al., 2017); yet, we could not identify prior research which examined the interactions or combinations among all three influences. We add to this literature by documenting these interacting effects for working mothers during young adulthood and in comparison to a number of other empirically-identified population sub-groups.

Using the CIT approach, we also identified that the interacting influences contributing to health behavior differences are much more complex for women than men. Few, if any, work and social circumstances contributed to differences for men; in contrast, parent status and employment status & hours were consistently relevant influences in differentiating women in terms of physical activity and time in bed. Such

conclusions were also supported in our sensitivity analyses, and lead to questions about gender equity. For instance, is it reasonable or fair that work and parent status differentiates time-dependent behaviors for women but not men? Are there perhaps differences in power and resources across gender that allow men to more uniformly address constraints from work and parenting, and if so, can those be equitably distributed to women? We add to the literature examining the multiple roles that women have to juggle (Gjerdingen, McGovern, Bekker, Lundberg, & Willemsen, 2000; McMunn, Bartley, Hardy, & Kuh, 2006; Yavorsky, Kamp Dush, & Schoppe-Sullivan, 2015), by demonstrating through data-driven processes that these things only mattered for women and not men in this young adult cohort. Results also provide additional insight into two time-dependent behavioral pathways that may explain prior associations between the imbalance from multiple social roles and poor health outcomes (Artazcoz, Borrell, & Benach, 2001; Dembe & Yao, 2016; Griep et al., 2016; Sabbath, Mejia-Guevara, Noelke, & Berkman, 2015).

Although there was evidence showing the vulnerability of working mothers across both outcomes, we also identified that full-time working men had the least amount of daily time in bed (7.8 daily hours). Actual sleep time may be as much as an hour less than daily time spent in bed among young adults (Youngstedt et al., 2016); as such, the full-time working men in this cohort may be on average obtaining less than the minimum recommendation of 7 daily hours and heightening their risk for a variety of chronic conditions (Itani et al., 2017). Moreover, two sub-groups of women—full-time working mothers and non-mothers working long full-time hours—displayed similar daily bedtime averages (8 h) compared to full-time working men. Coupled with other evidence that indicates women compared to men may have a longer period for falling asleep (Mallampalli & Carter, 2014) as well as stronger associations between inadequate sleep and chronic disease (Makarem & Aggarwal, 2017; Makarem et al., 2019), our results suggests that all three groups may have sleeping patterns that could be more harmful than estimates initially suggest.

We also identified employment status and work hours as an important factors in differentiating young adults' time-dependent health behaviors and that their influence depended on gender and other social circumstances. There are a number of political, economic, and other social forces (e.g., globalization, neoliberal politics, technology) that are changing the landscape of work and the experience of U.S. employment (e.g., increasing precarious employment) (Peckham, Baker, Camp, Kaufman, & Seixas, 2017; Schnall, Dobson, & Landsbergis, 2016). Such large-scale changes in work and employment need to be accompanied by large-scale understandings of their influences, and despite playing a significant role in this and other investigations (Caruso, Hitchcock, Dick, Russo, & Schmit, 2004; Dembe & Yao, 2016; Virtanen et al., 2009), work and its impact on time remains an under-assessed contributor to population health and health inequities (Ahonen, Fujishiro, Cunningham, & Flynn, 2018). This lack of attention is particularly salient given that this study identified important joint effects between work and other social circumstances on time-dependent health behaviors and that these differed by gender. As such, it appears that to reduce the gender inequalities in time-based health behaviors observed in this study, we will have to consider a number of factors including *work,* especially working time.

Strengths and limitations

A key limitation to our study was the use of self-reported time-dependent health behaviors. Given their susceptibility to reporting biases (e.g., recall, social desirability), outcomes may be aggregated and further shifted to recommended levels than if measured using more objective approaches (e.g., accelerometry), potentially underestimating relative differences between CIT sub-groups. However, prior research shows that reporting bias does not appear to systematically vary based on gender (Lauderdale, Knutson, Yan, Liu, & Rathouz, 2008; Sirard,

Hannan, Cutler, & Neumark-Sztainer, 2013), suggesting the rank interpretations (e.g., men achieve the most MVPA and working mothers the least) are likely reliable. In addition, the MVPA measure did not distinguish between leisure and occupation-related activity, limiting understanding of when/where men and women may be obtaining their differential levels of MVPA. Despite the cross-sectional analysis and lack of health outcome measures, which prevent endogeneity issues to be addressed, there are several study strengths worth noting. These include: the large sample size; examination of a variety of work, social circumstances, and social locations during the unique developmental period of young adulthood; as well as inclusion of sensitivity analyses to evaluate the robustness of our CIT results.

In terms of the CIT approach, there are two important considerations. First, CIT is a nonparametric approach (i.e., does not make assumptions about an underlying population distribution) and does not allow us to make statistical comparisons across final sub-groups in different partitions. Thus, study conclusions should be limited to this dataset and will require validation in other young adult cohorts. Second, input variables must be available for all participants, which limited the work and social circumstances we could examine (e.g., work shifts, occupation, industry and other child-related information was unavailable for certain participant groups, such as non-workers and non-parents).

Even so, there are numerous strengths to the CIT approach, including being statistically conservative and avoiding a host of pitfalls that accompany traditional linear regression (e.g., overfitting, covariate selection and order effects, multicollinearity risks, requiring a linear assumption about the relationship between variables (Nayak et al., 2018; Strobl et al., 2009; Venkatasubramaniam et al., 2017). While CIT offers such statistical advantages, these conservative decisions have trade-offs, as it may be misinterpreted that other social locations (e.g., race/ethnicity) and social circumstances (e.g., partner status among parents) are not important to these health behaviors. Instead, it is more appropriate to interpret the final sub-groups as the most robust for this cohort of participants, and that in a different sample of participants of a larger size, additional social locations and circumstances may rise to the level of differentiation necessary to meet these underlying statistical assumptions.

Finally, there are also many advantages of CIT over more familiar sub-group identification approaches (e.g., latent class analysis) including: being more easily interpretable; not requiring individual effects of predictors to be obscured; and eliminating the common second-step of having to associate the latent sub-groups with an outcome, as the associations with the outcome drives the CIT sub-group identification (Strobl et al., 2009; Venkatasubramaniam et al., 2017). CIT and other recursive partitioning approaches are increasingly being used to identify interacting influences and sub-groups across health outcomes (Lei, Nollen, Ahluwahlia, Yu, & Mayo, 2015; Nayak et al., 2018). Yet, much opportunity remains to leverage these less-familiar approaches in behavioral and population health.

Research, practice, and policy implications

Findings from this study suggest several implications for research, practice, and policy. In addition to studies to validate our findings, future investigations may benefit from using more objective measures of time-dependent health behaviors and identifying whether different dimensions of parent status (e.g., child age, number of children) are especially salient to constraining working mother's time. Research will also benefit from examining other behaviors essential for health (e.g., diet, eating behaviors) that have important but potentially more complicated relationships with time as well as exploring whether the interacting influences identified for MVPA and time in bed in young adulthood change or remain relevant at other developmental phases. In addition, the lack of differences by race/ethnicity in this study contradicted our expectations, given subtle and chronic forms of racism can differentially allocate time by race (Gee et al., 2019). Thus, future

research should unpack whether the lack of significance was a consequence of our methods (e.g., imbalanced sample sizes across racial/ethnic groups); of chronic experiences of racism being unrelated to time-dependent health behaviors; or if the amount of exposures have yet to accumulate to the degree by this life stage to show an effect.

If other studies reproduce our findings, then a shift is required to understand how to equitably address the heterogeneity in time-dependent health behaviors. One way to achieve this at a practice level may be to support the health of workers. To-date, most attempted efforts have occurred through workplace wellness programs (i.e., coaching or incentivizing employees to make individual behavior change (Pollitz & Rae, 2016), which have demonstrated negligible improvements for employee behavior, health, and organizational outcomes (Jones, Molitor, & Reif, 2019; Song & Baicker, 2019). While focusing on employee behavior change may be one relevant aspect, our findings coupled with this recent evidence suggests a focus on the role *work* itself (e.g., employment status quality, work hours) plays in everyday life may be necessary to effectively support employee behaviors that can translate to better organizational outcomes (e.g., job performance, medical spending).

A focus on all workers may help to yield population improvements, yet our findings also suggest a need for a targeted approach for working women, particularly those with children. Rather than focusing on individual women and their households as targets of change, we suggest inquiries into how workplace policies, public policies, and broader social norms can be modified to reduce the gender inequities in health behaviors we observed. While labor force participation and household responsibilities are often negotiated within hetero-families in gendered ways (Bianchi & Milkie, 2010), families also live in contexts where constraints from the labor force and unfriendly work-family polices are placed on them as a unit (Crosnoe & Dunifon, 2017). Thus, we may see more behavioral improvements at the population level and among those facing the greatest constraints if a focus is on equitably changing policy and culture. For instance, are there ways organizations can help to directly take the pressures off working mothers through offering on-site child care and ensuring equitable pay and resources (e.g., federal subsidies) to increase child care affordability? Are there ways to better protect full-time working parents of any gender, either through relaxed work hour requirements for full-time status, limiting work hours in sectors where long hours are enforced or normalized, or ways to shift persisting implicit and explicit gender norms about parenting (i.e., can full-time working fathers be supported in the workplace and in society-at-large to have time to care for their children without suffering pay or job consequences (Li, Kaiser, Pollmann-Schult, & Strazdins, 2019)? We propose that to observe the greatest improvements for the population overall and avoid further entrenching the unfavorable differences in time-dependent behaviors observed across gender it will be important to maintain this equitable lens as strategies are designed and trialed.

Ethical standards disclosure

Ethical permission was provided by the University of Minnesota's Institutional Review Board Human Subjects Committee. All participants gave informed consent prior to study participation.

Ethics approval

All protocols used for this study were approved by the University of Minnesota's Institutional Review Board Human Subjects Committee.

Declaration of competing interest

None.

CRediT authorship contribution statement

Megan R. Winkler: Conceptualization, Methodology, Writing - original draft. **Susan Telke:** Formal analysis, Methodology, Writing - review & editing. **Emily Q. Ahonen:** Conceptualization, Writing - review & editing. **Melissa M. Crane:** Conceptualization, Writing - review & editing. **Susan M. Mason:** Conceptualization, Writing - review & editing. **Dianne Neumark-Sztainer:** Funding acquisition, Project administration, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2020.100562.

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