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Sensing the impact of extreme heat on physical activity and sleep

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Abstract

Introduction: This study assesses the person-specific impact of extreme heat on low-income households using wearable sensors. The focus is on the intensive and longitudinal assessment of physical activity and sleep with the rising person-specific ambient temperature.

Methods: This study recruited 30 participants in a low-income and predominantly Black community in Houston, Texas in August and September of 2022. Each participant wore on his/her wrist an accelerometer that recorded person-specific ambient temperature, sedentary behavior, physical activity intensity (low and moderate to vigorous), and sleep efficiency 24 h over 14 days. Mixed effects models were used to analyze associations among physical activity, sleep, and person-specific ambient temperature.

Results: The main findings include increased sedentary time, sleep impairment with the rise of person-level ambient temperature, and the mitigating role of AC.

Conclusions: Extreme heat negatively affects physical activity and sleep. The negative consequences are especially critical for those with limited use of AC in lower-income neighborhoods of color. Staying home with a high indoor temperature during hot days can lead to various adverse health outcomes including accelerated cognitive decline, higher cancer risk, and social isolation.

Keywords

Extreme heat, accelerometer, physical activity, sleep, ambient temperature

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Introduction

In a changing climate, vulnerable groups such as older adults, low income, and those with chronic health conditions are at increased risk from extreme heat.[1–4] Previous work on extreme heat exposure largely has focused on mortality and morbidity data to discern the health impact of extreme heat.[4–6] They seldom examine and make use of physical and physiological information observed in people's daily living environment. Such information is valuable for establishing preventive measures and interventions to avoid harm from extreme heat.

The purpose of this study is to address this gap in extreme heat and health-related studies, and assess the impact of extreme heat on vulnerable groups such as the older adult and low-income household. Researchers have begun to use wearable sensors on outdoor workers and older adults to monitor continuously at the person-level physiological signals with the rising temperature.[7–9] They have, however, rarely integrated person-specific ambient temperature with physical/physiological conditions from

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extreme heat.[10,11] Outdoor air and land surface temperatures are often quite different from person-specific ambient temperatures due to factors including AC use, building materials, and ventilation.[12,13]

Studies relating extreme heat to health outcomes typically rely on local weather station monitoring and modeling.[14,15] They do not reflect individually experienced temperatures that vary widely within and between individuals.[16] Individuals move in and out of locations that are equipped with and without air conditioning (AC) and ventilation. While these small variations in one's microenvironment are important to ascertain the overall exposure level and its impact on health, they are not well established. This leads to exposure misclassifications by disregarding varying indoor temperatures and the urban heat island effect reflecting higher temperatures in urban areas compared to their surrounding areas.[17] Subsequently we will likely miss the real effects of extreme heat. Single threshold-driven heat warnings, thus, can be ineffective given such individual variabilities of heat experience.

The wrist-worn GENEActiv accelerometer we use contains a small temperature sensor that provides a practical solution to continuously monitor the temperature on the skin surface. The skin temperature differs from the relatively stable core body temperature and reflects their external thermal environment. Though the skin temperature is affected by an individual's core temperature, changes are dominated by interactions with ambient conditions.[18] The wrist is known to be the most susceptible to external thermal sensations.[19] We conducted a feasibility study using two iButton temperature sensors on nine participants.[20] We put two iButton sensors on the Fitbit watch. One sensor was on the side of the watch touching the skin and the other sensor was away from the skin. The study found that skin and near-air temperatures as measured by the wrist-worn Fitbit watch were highly correlated.

We build on our latest research using wearable sensors to assess the impact of extreme heat and demonstrate for the first time the role of physical activity and sleep. Extreme heat is known to affect the health of exposed individuals negatively by reducing physical activity[21–23] and disturbing sleep.[24–29] To identify varying effects of extreme heat on physical activity and sleep, longitudinal and precise assessments are necessary. Self-reported measures of physical activity and sleep do not offer accurate information to match with changing person-specific ambient temperature. The accelerometer-based objective measures distinguish sedentary and low levels of physical activity and provide precise measurements of sleep efficiency and sleep time. We use a well-validated, research-grade GENEActiv accelerometer[30] to measure continuously ambient temperature, physical activity, and sleep for multiple days and nights.

We hypothesize reduced physical activity and impaired sleep. We focus on low-income communities adversely affected by extreme heat and include an assessment of AC use that mitigates the person-specific ambient temperature. The impact of extreme heat is worse for low-income households and communities of color as they lack access to AC and live in lower quality housing. Even if households have AC, they may not use them often because of high utility costs.[31,32] We plan to expand this study to a larger cohort and help provide critical information in the development of evidence-based extreme heat intervention programs for low-income and older households largely situated within the communities of color.

Method

We recruited 30 participants in a low-income and predominantly Black community in Houston, Texas, in August and September of 2022 (Table 1). This is conducted in the participant's daily living environment.

Inclusion criteria: We recruited initially adults of 60 years and older and expanded later to all adults to facilitate recruitment. Participants live in a predominantly low-income and Black community, and can use or get help with online and/or smartphone-based app surveys. We hired a local nonprofit working with low-income communities to assist with recruitment and monitoring of participants. Each participant received monetary compensation for their two-week participation in the study. This study was approved by the Texas A&M Institutional Review Board committee (IRB2022-0735).

Participants were assigned a user ID code and a serial number for their respective accelerometer after completing the online informed consent and initial survey consisting of demographic, health, housing, and AC information. All accelerometers were configured to operate at 40 Hz and were given to participants at >95% battery life. The accelerometers automatically turn on at 05:00 the day prior to the start date. Accelerometers were configured to collect data for four weeks in order to provide a buffer to the study's two-week collection period.

A local project staff delivered accelerometers to participants one to three days prior to their start date. The battery was fully charged for a month, so participants did not need to remove the accelerometer from the wrist. They were asked to wear it on the wrist of their choice. After a two-week study period, the accelerometers were collected within five days to begin data extraction. Each accelerometer was extracted individually and converted into a .bin file. From there, each data file was trimmed to only account for data that occurred within the designated two-week study period. The data files were labeled with user IDs and start/end dates in order to maintain data integrity.

Data

Surveys were used to collect information on participants' age, sex, race, income status, and housing conditions. The

Table 1. Participant demographic and AC use information.

Category	count (distinct)	count (%)
n	30	
Gender		
Males	9	30.0
Females	21	70.0
Age	58.23	
<40	5	16.7
40–49	1	3.3
50–59	10	33.3
60–69	5	16.7
70–75	6	20.0
76+	3	10.0
Race		
African American	23	76.7
Latino or Hispanic	5	16.7
Two or more	1	3.3
White	1	3.3
Education level		
High school	10	33.3
Less than high school	2	6.7
Some college	12	40.0
Bachelor's (or equivalent)	4	13.3
Income level		
$9999 or less	10	33.3
$10,000 to $14,999	6	20.0
$15,000 to $24,999	4	13.3
$25,000 to $34,999	5	16.7
$35,000 to $49,999	3	10.0
$50,000 to $74,999	1	3.3
$75,000 or more	1	3.3
How often do you use your air conditioning?		
No air conditioning available	1	3.3
Used at least once a month	1	3.3
Used at least once every few days	3	10.0
Used at least once every day	25	83.3

AC use was classified as "frequent" if the participants responded, "Used at least once every day," and "infrequent" otherwise.

The wrist-worn GENEActiv accelerometer was used to record person-specific ambient temperature, physical activity, and sleep 24 h over 14 days for each participant.

Person-specific ambient temperature was summarized as per-day overall temperature.

Outside temperature information for each day was determined based on historical weather data using participants' zip codes.[33] The temperatures varied from 25° to 38° across study days with a median of 34° and an interquartile range of 32°–35°.

Physical activity and sleep were processed from the raw movement data using GENEActiv default R markdown analysis tools. The processed data included nonwear times, per day (3 p.m. to 3 p.m.) durations of sedentary, light, moderate, and vigorous activity, total sleep time, and sleep efficiency per day. For each day, the proportion of sedentary time was calculated as total sedentary time divided by total wear time and translated into percentages. Sleep efficiency was defined as ([total sleep time]/[time in bed]) × 100. Any days with less than 12 h of wear time or with data quality issues (estimated sleep efficiency of zero) were excluded from the analyses.

After actigraphy data processing, activity and sleep information was available on 29 participants over a total of 438 days, ranging from 6 to 19 days of data per participant.

Statistical analyses

Mixed-effect linear regression models were fit on participant-day level data to conduct within-person and between-person analyses. The participant-specific random intercept was used to account for between-participant baseline differences in response variables, as well as to account for correlation across days for the same participant.

To assess the effect of heat exposure on physical activity, Model 1 used the participant-day percentage of sedentary time as the response. Age, sex, race, day type (weekday vs weekend) and participant-day person-specific ambient temperature were used as fixed covariates. To assess the effect of extreme heat exposure on sleep impairment**,** Model 2 used participant-day sleep efficiency as the response. Age, sex, race, day type (weekday vs weekend) and participant-day person-specific ambient temperature were used as fixed covariates. We also included participant-day percent of the sedentary time as a fixed covariate in Model 2 because sleep could also be affected by physical activity. For both Models 1 and 2, we conducted a sensitivity analysis to validate whether the effect of person-specific ambient temperature was linear by comparing Akaike Information Criterion (AIC) values between the linear mixed model and generalized additive mixed model, and used penalized regression splines to estimate the effect of person-specific ambient temperature.[34] The best model was selected as the one with the smallest value of AIC.

To assess the effect of AC use on person-specific ambient temperature as a function of outside temperature, Model 3 used participant-day person-specific ambient temperature as the response. Age, sex, race, frequency of AC use, day type (weekday vs weekend) and participant-day outside temperature were used as fixed covariates. We also considered models that include interactions between outside temperature and AC use, outside temperature and age, day type and AC use, and day type and outside temperature as fixed covariates. The best model was selected based on the smallest value of AIC.

All linear mixed-effect models were fit using R package nlme,[35] and all generalized additive mixed models were fit using R package mgcv.[36] p-value < .05 was considered statistically significant. All analyses were performed in R statistical software version 4.1.2.

Results

Model 1: Association between sedentary time and person-specific ambient temperature. Based on the linear mixed-effects model, the person-specific ambient temperature had a significant effect on the percent of sedentary time (p-value < .0001), with a 1° increase in ambient temperature leading to around 2% ($\beta_{temp} = 2.11$) increase in the percent of time spent sedentary. The effects of age, sex, day type, and race were not significant. Comparing AIC values between the linear model (AIC = 3147) and the generalized additive model (AIC = 3072) confirmed that the additive model provided a better fit to the data, with p-value < .0001 for person-level ambient temperature, and a borderline significant effect of age (p-value = .0450 with an effect size of 2.1% increase in sedentary time for every 10 years of age). The effect of sex was significant, with men having a 7.7% increase in sedentary time compared to women. The effects of day type and race were not significant. Figure 1 shows the predicted percentage of sedentary time as a function of person-specific ambient temperature with 95% confidence interval. To illustrate the effect of age, the black line corresponds to age = 70 years (75th percentile), and the blue line corresponds to age = 35 years (10th percentile). While the effect is linear from 25° to 30°, it levels off afterward, suggesting that an increase in person-specific ambient temperature beyond 30° does not provide a further increase in sedentary time, resulting in a nonlinear effect.

Model 2: Association between sleep efficiency and person-specific ambient temperature. Based on the linear mixed effects model, the person-specific ambient temperature had a significant effect on sleep efficiency (p-value = .0337), with a 1° increase in person-level ambient temperature leading to around 2% ($\beta_{temp} = -1.8$) decrease in sleep efficiency. The effects of age, sex, day type, race, and percentage spent sedentary were not significant. Comparing AIC values between the linear model (AIC = 3920) and the generalized additive model (AIC = 3903) confirmed that the additive model provided a better fit to the data, with p-value = .0073 for ambient temperature. The effects of age, sex, day type, race, and percentage spent sedentary were not significant. Figure 2 shows the predicted sleep efficiency as a function of person-level ambient temperature with 95% confidence interval. The values of fixed covariates were set to match the values in Model 1 (sex = female, race = African American), and the percentage of sedentary time was set at 50% (average across all participants). The predicted responses for age = 70 (black) and age = 35 (blue) overlap as the estimated effect size is small ($\beta_{age} = 0.06$) and not significant (p-value = .719). The shape of the estimated curve suggests that the effect of person-specific ambient temperature is

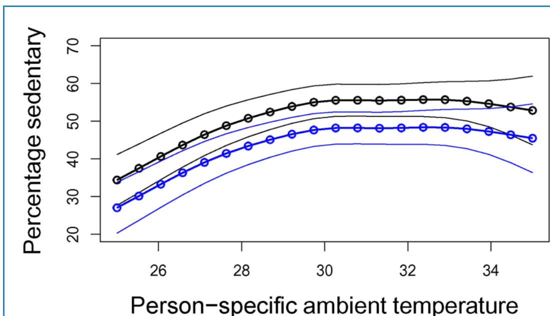

Figure 1. The predicted percentage of sedentary time as a function of person-specific ambient temperature (with 95% CI) for age = 70 (black) and age = 35 (blue) based on Model 1.

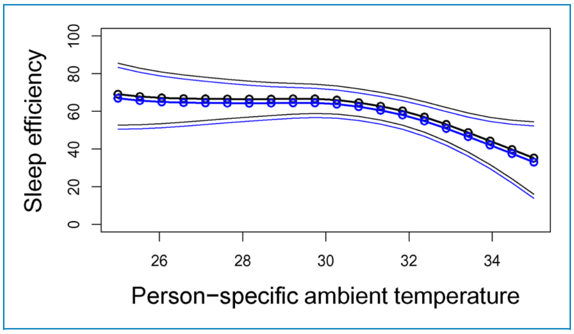

Figure 2. The predicted sleep efficiency as a function of person-specific ambient temperature (with 95% CI) on sleep efficiency for age = 70 (black) and age = 35 (blue) based on Model 2. The lines overlap as the estimated effect size for age was small (β_{age} = 0.06) and not significant (*p*-value = .719).

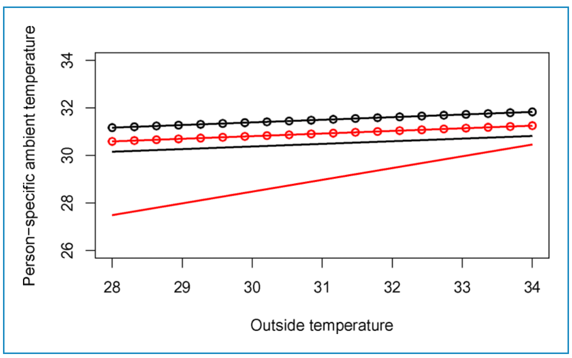

Figure 3. The predicted person-specific ambient temperature as a function of outside temperature for weekday (black) and weekend (red) separated by AC use (straight−frequent, pointed−infrequent) based on Model 3. Age effect is not shown as it was not significant after adjusting for the day type (*p*-value = .2475) with a small estimated effect size (β_{age} = 0.02). A significant interaction exists between AC use and day type, with a stronger correlation between person-specific ambient and outside temperatures with frequent AC use on the weekends (red straight line) compared to weekdays (black straight line).
AC: air conditioning.

strongest when moving from 32° to 35°; thus, the effect is nonlinear.

Model 3: Association between outside temperature, AC use, and person-specific ambient temperature. Using the AIC criterion for model selection of appropriate interaction terms led to the model that included an interaction between day type and AC use and an interaction between the outside temperature, day type, and AC use (AIC = 1420). The main effect of outside temperature was significant (*p*-value < .0001). The main effects for AC use (*p*-value = .1211) and day type (p-value = 0.0671) were not significant but had a significant pairwise interaction effect (p-value = .0002). The interaction between the outside temperature, day of the week, and AC use was also significant (*p*-value = .0001). The effects of age, sex, and race were not significant.

To facilitate the interpretation of effects sizes in the presence of significant interactions, Figure 3 displays predicted person-specific ambient temperature as a function of outside temperature stratified by AC use (straight lines for frequent, pointed lines for infrequent) and day type (black = weekday, red = weekend). When AC use is infrequent, there is little difference between weekday and weekend ($\beta_{weekend} = -0.58$), and the person-specific ambient temperature is estimated to be overall quite high (31°–32°). However, when AC use is frequent, there is a clear difference in association between weekdays and weekends. On weekdays, the frequent use of AC leads to an estimated decrease of 1° in person-specific ambient temperature, bringing it to an average of 30°. The association between person-specific ambient temperature and outside temperature, while significant, is not very strong ($\beta_{temp} = 0.11$). In contrast, on weekends, the frequent use of AC leads to a significant reduction in person-specific ambient temperature compared to the infrequent use, and also a significantly stronger association between outside temperature and ambient temperature ($\beta_{temp} = 0.49$).

Overall, frequent AC use implies lower person-specific ambient temperature; however, the effect size varies significantly depending on the day type (weekday vs weekend), and the range of outside temperature. The effect of AC use is the strongest on the weekends, and when outside temperatures are less extreme. Specifically, AC use makes a greater difference to person-specific ambient temperature when the outside temperature is moderate (28°), and less difference when the outside temperature is higher (34°). Overall, there is a significant difference in how the outside temperature affects the person-specific ambient temperature based on day type and AC use.

Discussion

As hypothesized, with the rising temperature, physical activity is reduced. This result corroborates other study findings that report decreased step counts[37] and reduced participation in outdoor activities including park visits during hot summer days.[38] What is novel with the use of the accelerometer is the segmentation of physical activity into light, moderate, vigorous, and sedentary dimensions. This segmentation demonstrates greater precision regarding the intensity of physical activities, which is critical for older adults as sedentary and light activities can be pervasive. We find increased sedentary behavior with the rising person-specific ambient temperature. This is an important finding given the emerging evidence that sedentary behavior is a risk factor for cognitive decline.[39] Sedentary behavior is associated with lower executive function test scores.[40] Residents with high cognitive impairment spent the highest proportion of their daytime activity in sedentary behavior[41]; and greater sedentary time was associated with lower cerebral blood flow.[42] Furthermore, sedentary behavior resulting in weight gain and obesity is associated with cancer risk.[43–45] Moderate to vigorous physical activity lowers cancer risk by preventing chronic inflammation and insulin resistance, improves immune function, and reduces oxidative stress and sex hormones.[46–48]

Results also support the well-proven thesis that extreme heat is associated with poor sleep health. A systemic review between 1980 and 2017 showed that total sleep times declined, and sleep disruption rose among the older adult and low-income residents in summer.[49] Another study collected sleep data for five days using the wrist-worn accelerometer and compared them with bedroom temperature and humidity. Sleep efficiency was lower in the summer than in the winter or fall.[50] They also found increased wakefulness during summer compared to winter. Our result provides a more precise estimate of reduced sleep efficiency and complements existing studies that demonstrate decreased sleep quantity and quality.

Finally, the role of AC in mitigating the effects of extreme heat cannot be overemphasized as seen in the difference between outside and person-specific ambient temperature in our finding. It is unclear why the effect of AC use on person-specific ambient temperature is higher on the weekend compared to the weekdays. Because location information and AC use are unavailable on a daily basis in the model, it is difficult to interpret these results. To resolve this issue, obtaining geocoded information using an app-based survey with a question on daily AC use and complementing the survey with household-level smart meter data are options. These options help match the fine-grained digital data from the accelerometer and strengthen personalized assessments of extreme heat impact.

Limitations

It is a relatively small sample in terms of age and gender distributions. This is also not a representative sampling but a purposeful one given the study's focus on low-income households with a higher variability of AC use. It is, thus, premature to draw a generalization of our findings. More investigation is needed to understand the nonlinearities demonstrated in both physical activity and sleep associated with the rising person-specific ambient temperature. A larger cohort with additional measures of confounders including comorbidities and chronic health conditions would shed light on this issue. Adding interviews will also help evaluate the participants' (mal)adaptive behavior during the hottest days of the summer and understand findings better.

Conclusion

Though the use of AC is pervasive in the southern part of the United States, the study shows high variabilities in person-specific ambient temperature despite relatively uniform outdoor temperature. This is due largely to the varying use of AC coupled with poorer housing conditions in the low-income neighborhood that we draw our participants from. Our findings confirm objectively what we know intuitively and with self-reported responses. That is, the elevated person-specific ambient temperature increases sedentary behavior and decreases sleep efficiency.

We expect the older adult in low-income communities to be the most vulnerable target to extreme heat. Older adults become less mobile with chronic illnesses. The lack of exercise because of hot weather often worsens their pre-existing health conditions. In addition, reduced activity and sleep disturbance are likely to amplify cancer risk and deficits in mild cognitive impairment and Alzheimer's disease and related dementias during extreme heat events.[51–53] As such, it is important to assess the role of hot weather in the development of multiple adverse health outcomes such as accelerating cognitive decline, worsening preexisting health conditions, and precipitating social isolation due to confinement at home.

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Guarantor: SC.

Contributorship: SC designed the study, recruited participants, and wrote the text and IG designed statistical methods, performed statistical analysis, wrote statistical analysis and results, and created figures.

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References

1. Tuholske C, Caylor K, Funk C, et al. Global urban population exposure to extreme heat. *Proc Natl Acad Sci USA* 2021; 118: e2024792118.
2. McKenna ZJ, Foster J, Atkins WC, et al. Age alters the thermoregulatory responses to extreme heat exposure with accompanying activities of daily living. *J Appl Physiol* 2023; 135: 445–455.
3. Tham S, Thompson R, Landeg O, et al. Indoor temperature and health: a global systematic review. *Public Health* 2020; 179: 9–17.

4. Vaidyanathan A, Malilay J, Schramm P, et al. Heat-related deaths—United States, 2004–2018. *Morb Mortal Wkly Rep* 2020; 69: 729.
5. Shindell D, Zhang Y, Scott M, et al. The effects of heat exposure on human mortality throughout the United States. *GeoHealth* 2020; 4: e2019GH000234.
6. Lüthi S, Fairless C, Fischer EM, et al. Rapid increase in the risk of heat-related mortality. *Nat Commun* 2023; 14: 4894.
7. Shakerian S, Habibnezhad M, Ojha A, et al. Assessing occupational risk of heat stress at construction: a worker-centric wearable sensor-based approach. *Saf Sci* 2021; 142: 105395.
8. Bailey E, Fuhrmann C, Runkle J, et al. Wearable sensors for personal temperature exposure assessments: a comparative study. *Environ Res* 2020; 180: 108858.
9. Runkle JD, Cui C, Fuhrmann C, et al. Evaluation of wearable sensors for physiologic monitoring of individually experienced temperatures in outdoor workers in southeastern US. *Environ Int* 2019; 129: 229–238.
10. Pham S, Yeap D, Escalera G, et al. Wearable sensor system to monitor physical activity and the physiological effects of heat exposure. *Sensors* 2020; 20: 855.
11. Cheong SM, Bautista C and Ortiz L. Sensing physiological change and mental stress in older adults from hot weather. *IEEE Access* 2020; 8: 70171–70181.
12. Vant-Hull B, Ramamurthy P, Havlik B, et al. The Harlem heat project: a unique media–community collaboration to study indoor heat waves. *Bull Am Meteorol Soc* 2018; 99: 2491–2506.
13. Nazarian N and Lee JK. Personal assessment of urban heat exposure: a systematic review. *Environ Res Lett* 2021; 16: 033005.
14. Nguyen JL, Schwartz J and Dockery DW. The relationship between indoor and outdoor temperature, apparent temperature, relative humidity, and absolute humidity. *Indoor Air* 2014; 24: 103–112.
15. Gao C, Kuklane K, Östergren PO, et al. Occupational heat stress assessment and protective strategies in the context of climate change. *Int J Biometeorol* 2018; 62: 359–371.
16. Mistry MN, Schneider R, Masselot P, et al. Comparison of weather station and climate reanalysis data for modelling temperature-related mortality. *Sci Rep* 2022; 12: 5178.
17. Kuras ER, Hondula DM and Brown-Saracino J. Heterogeneity in individually experienced temperatures (IETs) within an urban neighborhood: insights from a new approach to measuring heat exposure. *Int J Biometeorol* 2015; 59: 1363–1372.
18. Stewart ID and Mills G. *The urban heat island*. Amsterdam, NL: Elsevier, 2021.
19. Romanovsky AA. Skin temperature: its role in thermoregulation. *Acta Physiol* 2014; 210: 498–507.
20. Choi JH and Loftness V. Investigation of human body skin temperatures as a bio-signal to indicate overall thermal sensations. *Build Environ* 2012; 58: 258–269.
21. Aspvik NP, Viken H, Ingebrigtsen JE, et al. Do weather changes influence physical activity level among older adults?–The generation 100 study. *PloS one* 2018; 13: e0199463.
22. Obradovich N and Fowler JH. Climate change may alter human physical activity patterns. *Nature Human Behaviour* 2017; 1: 0097.
23. Balmain BN, Sabapathy S, Louis M, et al. Aging and thermoregulatory control: the clinical implications of exercising under heat stress in older individuals. *BioMed Res Int* 2018; 2018.
24. Lan L, Tsuzuki K, Liu YF, et al. Thermal environment and sleep quality: a review. *Energy Build* 2017; 149: 101–113.
25. Rifkin DI, Long MW and Perry MJ. Climate change and sleep: a systematic review of the literature and conceptual framework. *Sleep Med Rev* 2018; 42: 3–9.
26. Minor K, Bjerre-Nielsen A, Jonasdottir SS, et al. Ambient heat and human sleep. arXiv preprint arXiv:2011.07161. 2020 Nov 13.
27. Okamoto-Mizuno K, Tsuzuki K and Mizuno K. Effects of mild heat exposure on sleep stages and body temperature in older men. *Int J Biometeorol* 2004; 49: 32–36.
28. Wang C, Liu K and Wang H. The effects of temperature on sleep experience: evidence from China. *Appl Econ* 2022: 1–7.
29. Tsuzuki K, Mori I, Sakoi T, et al. Effects of seasonal illumination and thermal environments on sleep in elderly men. *Build Environ* 2015; 88: 82–88.
30. https://activinsights.com/expertise/publications/ accessed on Jan. 7, 2024.
31. Hoffman JS, Shandas V and Pendleton N. The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas. *Climate* 2020; 8: 12.
32. Ortiz L, Gamarro H, Gonzalez JE, et al. Energy burden and air conditioning adoption in New York city under a warming climate. *Sustainable Cities and Society* 2022; 76: 103465.
33. NOAA. *National Centers for Environmental Information*. https://www.ncei.noaa.gov/products/land-based-station/nclimgrid-daily accessed February 2023.
34. Wood SN. *Generalized additive models: an introduction with R*. Boca Raton, FL: CRC press, 2017.
35. Pinheiro J and Bates D. *Mixed-effects models in S and S-PLUS*. New York, NY: Springer Science & Business Media, 2006.
36. Wood SN. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 2011; 73: 3–6.
37. Ho JY, Goggins WB, Mo PK, et al. The effect of temperature on physical activity: an aggregated timeseries analysis of smartphone users in five major Chinese cities. *International Journal of Behavioral Nutrition and Physical Activity* 2022; 19: 68.
38. Kabisch N and Kraemer R. Physical activity patterns in two differently characterised urban parks under conditions of summer heat. *Environ Sci Policy* 2020; 107: 56–65.
39. Wheeler MJ, Dempsey PC, Grace MS, et al. Sedentary behavior as a risk factor for cognitive decline? A focus on the influence of glycemic control in brain health. *Alzheimer's & Dementia: Translational Research & Clinical Interventions* 2017; 3: 291–300.
40. Vásquez E, Strizich G, Isasi CR, et al. Is there a relationship between accelerometer-assessed physical activity and sedentary behavior and cognitive function in US Hispanic/Latino adults? The Hispanic community health study/study of Latinos (HCHS/SOL). *Prev Med* 2017; 103: 43–48.
41. Marmeleira J, Ferreira S and Raimundo A. Physical activity and physical fitness of nursing home residents with cognitive impairment: a pilot study. *Exp Gerontol* 2017; 100: 63–69.
42. Zlatar ZZ, Hays CC, Mestre Z, et al. Dose-dependent association of accelerometer-measured physical activity and sedentary time with brain perfusion in aging. *Exp Gerontol* 2019; 125: 110679.
43. Friedenreich CM, Ryder-Burbidge C and McNeil J. Physical activity, obesity and sedentary behavior in cancer etiology:

epidemiologic evidence and biologic mechanisms. *Mol Oncol* 2021; 15: 790–800.

44. Biller VS, Leitzmann MF, Sedlmeier AM, et al. Sedentary behaviour in relation to ovarian cancer risk: a systematic review and meta-analysis. *Eur J Epidemiol* 2021: 1–12.
45. Nguyen LH, Liu PH, Zheng X, et al. Sedentary behaviors, TV viewing time, and risk of young-onset colorectal cancer. *JNCI cancer spectrum* 2018; 2: pky073.
46. McTiernan A. Mechanisms linking physical activity with cancer. *Nat Rev Cancer* 2008; 8: 205–211.
47. Thune INGER and Furberg AS. Physical activity and cancer risk: dose-response and cancer, all sites and site-specific. *Med Sci Sports Exercise* 2001; 33: S530–S550.
48. de Boer MC, Wörner EA, Verlaan D, et al. The mechanisms and effects of physical activity on breast cancer. *Clin Breast Cancer* 2017; 17: 272–278.
49. Okamoto-Mizuno K and Tsuzuki K. Effects of season on sleep and skin temperature in the elderly. *Int J Biometeorol* 2010; 54: 401–409.
50. Rifkin DI, Long MW and Perry MJ. Climate change and sleep: a systematic review of the literature and conceptual framework. *Sleep Med Rev* 2018; 42: 3–9.
51. Hartman YA, Karssemeijer EG, van Diepen LA, et al. Dementia patients are more sedentary and less physically active than age-and sex-matched cognitively healthy older adults. *Dement Geriatr Cogn Disord* 20184; 46: 81–89.
52. Walker KA, Power MC and Gottesman RF. Defining the relationship between hypertension, cognitive decline, and dementia: a review. *Curr Hypertens Rep* 2017; 19: 1–6.
53. Peter-Derex L, Yammine P, Bastuji H, et al. Sleep and Alzheimer's disease. *Sleep Med Rev* 2015; 19: 29–38.