Opportunities and Challenges in Identification and Classification of Heat Stress Risk Based on Analysis of Individual and Neighborhood Level Factors

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ABSTRACT

Heat-related illnesses and deaths are significant public health problems. Extreme heat is the No.1 deadliest form of weather on average in 1990-2019 in the US according to the National Weather Service. Measurements and forecasts made at regional weather stations are a common data source of Heatwave Early Warning Systems. However, regional weather stations provide inaccurate estimates of the heat index that people experience in different microclimates. Introducing a direct measurement of heat index experienced by individuals via wearable sensors will allow more accurate exposure assessment and identification of factors associated with dangerous exposures to extreme heat. The goal of this dissertation is to characterize the individually experienced heat index exposure via wearable sensors in an urban and a rural location in summer in a southern part of the United States. In the first study, 51 outdoor workers in Birmingham, Alabama wore a small thermometer attached to their shoe. Their occupational Wet Bulb Globe Temperatures (WBGT), a comprehensive heat exposure index, was estimated from either temperature from the shoe thermometers or nearby weather stations. In the second and third studies, 88 urban participants and 89 rural participants completed a seven-day intervention where they performed normal activity on Days 1-2 and spent an additional 30 minutes outdoors daily on Days 3-7. Participants wore a small thermometer attached to the shoe and a pedometer at their waist to track steps. Neighborhood hygrometers/thermometers were deployed close to participants' homes to measure neighborhood level heat indexes. In the fourth study, we conducted a phone survey including 101 participants in the same urban and rural locations to examine how their heat-health behaviors changed due to COVID-19 and high profiles of police brutality cases in Summer 2020 compared to previous summers. The results demonstrated that (1) a wearable thermometer on the shoe was a feasible way to measure individually experienced temperatures; (2) among outdoor workers, WBGT from shoe thermometer temperatures estimated more hours in dangerous exposure categories and recommended more protective work-rest schedules compared to WBGT from weather station temperatures; (3) neighborhood level heat indexes improved the prediction of individually experienced heat indexes compared to weather station data alone; (4) rural participants experienced higher heat index exposures than urban participants, after accounting for ambient conditions; (5) spending a small amount of additional time outdoors was a feasible and effective intervention where participants walked more steps and had lower individually experienced heat indexes during the intervention days compared to baseline days; (6) a significantly lower percent of participants reported they would use public cooling centers in Summer 2020 compared to previous summers. Taken together, the results of these studies identified methods for more accurate heat exposure assessment and its application in monitoring heat-safety while promoting physical activity via time spent outdoors in the summer. Future work could incorporate physiological response monitoring linked to simultaneous individually experienced heat exposure to further characterize exposure-response relationships across different populations. Additionally, a longer intervention and more advanced wearable devices such Fitbit, Apple

Watches could be used to monitor sustainability of the intervention and intervention benefits beyond short term increases in physical activity, respectively.

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GENERAL AUDIENCE ABSTRACT

Extreme high temperatures/humidity can bring dangerous adverse effects in people. Extreme heat is on average the deadliest form of weather in 1990-2019 in the US estimated by National Weather Service. Heatwave Early Warning Systems are introduced to closely monitor extreme heat events, estimate the magnitude of health consequences due to extreme heat, send warning messages to vulnerable populations, and trigger response plans to reduce the dangerous health effects of heat. Heatwave Early Warning Systems generally rely on the measurement and forecasts from regional weather stations. However, the temperature/humidity measurements made at weather stations can be different from the temperature/humidity people experience. People can live far away from weather stations and they move through indoor and outdoor locations, where weather station measurements will not represent temperatures experienced, particularly in climate-controlled indoor settings. Therefore, we recruited participants in an urban and a rural location and had each participant wear a small thermometer clipped to their shoe to directly measure the temperature they experienced as they went about their normal activities. In the first study, 51 outdoor workers wore this small thermometer on their shoe at work. We calculated a comprehensive heat exposure index from either the shoe thermometer temperatures or nearby weather station temperatures. In the second and third studies, 88 urban participants and 89 rural participants completed a seven-day intervention where they performed normal activities on Days 1-2 and spent an additional 30 minutes outdoors daily on Days 3-7. Participants wore the small thermometer clipped to the shoe and a pedometer at their waist to track how many steps they walked. We placed temperature/humidity sensors close to participants' homes to take measurements at a neighborhood level. In the fourth study, we conducted a phone survey including 101 participants in the same urban and rural locations to examine whether they had different cooling methods due to the COVID-19 pandemic and high profiles of police brutality cases in Summer 2020 compared to previous summers. The results demonstrated that (1) a small thermometer clipped on the shoe was a feasible way to measure temperatures at the individual level; (3) among outdoor workers, the comprehensive heat exposure index using temperatures from the shoe thermometers estimated more hours when outdoor workers were at a risk of dangerous exposure to extreme heat, and it recommended more rest time for workers to cool off compared to using weather station temperatures alone; (3) neighborhood level temperature/humidity was more representative of the temperatures recorded from thermometers on the shoe compared to nearby weather stations; (4) rural participants experienced higher temperature/humidity than urban participants, even when their nearby weather station temperature measurements were the same; (5) spending a small amount of additional time outdoors is a feasible and effective intervention where participants walked more steps and experienced lower temperature/humidity during the intervention days compared to baseline days; (6) a smaller number of participants reported they would use public cooling centers/spaces (*e.g.*, air-conditioned library, air-conditioned churches, waterparks) to cool down due to fear of contracting COVID-19 and safety concerns brought by the high profiles of police brutality cases in Summer 2020 compared to previous summers. Taken together, the results of these studies

showed that the wearable thermometers clipped on the shoe could provide more accurate assessment of temperatures experienced by participants compared to weather stations. This method could be used in future outdoor time interventions to monitor and ensure participants safely spend time outdoors while minimizing the risk of heat-related illness. In future work, more advanced sensors (*e.g.*, Fitbit, Apple Watch) can be worn by participants to measure physiological responses across different temperatures experienced. Additionally, a longer intervention time can be used to test if participants would continue to spend additional time outdoors.

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ATTRIBUTIONS

Manuscript 1: Suwei Wang contributed to the methodology, investigation, formal analysis, visualization with oversight from Julia Gohlke. Suwei Wang was a major contributor in the original draft writing. All authors reviewed and approved the final manuscript.

Manuscript 2: Suwei Wang contributed to the methodology, investigation, data curation, formal analysis, programming, visualization with oversight from Julia Gohlke. Suwei Wang was a major contributor in the original draft writing. All authors reviewed and approved the final manuscript.

Manuscript 3: Suwei Wang contributed to the methodology, investigation, data curation, formal analysis, programming, visualization with oversight from Julia Gohlke. Suwei Wang was a major contributor in the original draft writing. All authors reviewed and approved the final manuscript.

Manuscript 4: Suwei Wang contributed to the investigation, data curation, formal analysis, programming, visualization with oversight from Julia Gohlke. Suwei Wang was a major contributor in the original draft writing. All authors reviewed and approved the final manuscript.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Introduction

1.1 Exposure to extreme heat is a significant public health problem

Deaths attributable to weather-related extreme heat exposure is a significant and continuing public health problem. Extreme heat is the No.1 deadliest form of extreme weather according to the National Weather Service [1]. More than 166,000 people died due to extreme heat globally in 1998-2017, including over 70,000 deaths during the heatwave in 2003 in Europe and over 56,000 deaths in the heatwave in 2010 in the Russian Federation [2]. In the US alone, a total of 6,220 deaths with heat as the underlying cause and 4,307 deaths with heat as the contributing cause were reported in death records in 2004-2018 [3]. However, the number of heat-related deaths may be underestimated. Most studies pull data from death records using the International Classification of Diseases (ICD), Ninth/Tenth Revision cause-of-death codes, while deaths from another cause (*e.g.*, cardiovascular disease) where heat may be a contributing factor are rarely counted, underestimating the total burden of heat-related mortality [3-5]. The Centers for Disease Control and Prevention (CDC) used death records included those listing ICD-10 codes X30 (exposure to excessive natural heat), P81.0 (environmental hyperthermia of newborn), or T67 (effects of heat and light) as the underlying or as one of the contributing causes of deaths and estimated that on average 702 people died from high temperatures each year between 2004-2018 in the US [3]. However, Weinberger *et al.* (2020) estimate that about 5,600 people died from high temperatures per year in 1997-2006 in the US by using a regression-based method regardless of the assigned cause of death in 297 US counties [6], contrasting to the CDC's 702 yearly estimation.

In addition to deaths, extreme heat causes health problems ranging from rashes and cramps to heat exhaustion and heat stroke [7]. Each year, there are more than 65,000 emergency room

visits and 8,992 hospitalization due to extreme heat in the US [8]. Evidence shows there are associations between high outdoor temperatures and health outcomes, including hospital admissions, emergency room visits, and ambulances requests, particularly in occupational settings [9]. Gronlund *et al.* (2014) found that extreme heat is associated with increased hospital admissions, especially for renal (15%; 95% confidence interval: 9-21%) and respiratory diseases (4%; 95% confidence interval: 2-7%) among the elderly in the US [10]. Anderson *et al.* (2013) found that for every 10°F increase in temperature on the same day, the respiratory hospital admission rate increases by 4% in 213 counties in the US [11]. During the heatwaves in North Carolina in 2008-2011, there were an average of 15.8 more daily visits to emergency department at the city level for every 1°F increase from 98-100°F [12].

While people may be less exposed to extreme heat due to better infrastructure and higher prevalence of air conditioning, evidence suggests that risk of heat-related morbidity and mortality will increase in the future due to climate change [13-15]. A study of 12 major US cities projected that there will be approximately 200,000 heat-related deaths by the end of 21st century due to increasing temperatures, even after accounting for increased human resiliency to extreme heat [16]. Therefore, protecting the public from heat-related illness and deaths is important and urgent.

This dissertation is built on a ten-year academic-community partnership, ENACT (www.enactalabama.org), to study the heat exposure among residents in Alabama, US. ENACT connects community organizations of Friends of West End (FoWE) in Birmingham, AL, and West Central Alabama Community Health Improvement League (WCACHIL) in Wilcox County, AL and researchers from Virginia Tech, University of Alabama at Birmingham, and Johns Hopkins University [17]. Community leaders were engaged in participant recruitment,

study design and implementation, investigation, results dissemination back to local residents in the works in this dissertation.

1.2 Effectiveness of the current heatwave early warning systems

With climate change, it is expected that heatwaves will become more common, more severe and longer lasting [18]. Heatwave early warning systems have been introduced to reduce avoidable consequences of extreme heatwaves on human health by forecasting heatwave events, predicting possible health outcomes, and promptly notifying preventive measures to people who are vulnerable to heat [19]. Heatwave early warning systems rely on temperature and humidity forecasts made at regional weather stations (WS) to trigger effective and timely response plans [19-21]. Weather station measurements are indirect measurements of the heat exposure of populations nearby. The systems usually do not consider microclimate variations, although an experimental HeatRisk forecast product developed by the National Weather Service provides a more refined heat risk guide for the western states of the US [22]. Moreover, these systems do not consider the heat exposure variations caused by people moving between indoors and outdoors or additional individual vulnerability factors including acclimatization, dehydration, medications, health conditions, clothing, and metabolic heat, *etc.* [23]. Higher metabolic heat generated through activities can bring dangerous heat-related effects even when the outdoor environment is not high enough to trigger alerts. For example, a study on the deaths of American football players found that 100% of heat-related deaths occurred without triggering an alarm from the National Weather Service [24]. As the first step in understanding the importance of changes in exposure levels in predicting population risks, more precise measurement of individual exposure levels is required. In Chapter 2-4, we collect direct measurements of temperature exposure at the individual level via wearable sensors instead of solely relying on the

indirect regional weather station measurements. We aim to quantify the differences between individually measured heat index exposure and weather station measurements to improve accuracy of heat exposure assessment.

1.3 Vulnerability to heat exposure and heat-related illness

To adapt to the ever-increasing extreme heat in the changing climate, it is necessary to know exactly which populations are most vulnerable to the health effects of extreme heat [9]. While heat-related health effects are preventable, people's behaviors and/or ability to reduce their heat exposure are usually patterned by their socioeconomic status and cultural factors [9]. For example, one study shows that people living in census blocks groups with lower socioeconomic status and higher % self-reported Hispanic, Native American, African American, and Asian American populations were more likely to live in warmer neighborhoods with less vegetation cover in Phoenix, Arizona [25]. Another study found zipcode level % in poverty and % with high school diploma were significant effect modifiers of the relationship between death and extreme heat across 135 cities in the US [26]. This study also showed individual level race identified as nonwhite within the Medicare claims dataset was a significant effect modifier of the relationship between extreme heat and death [26]. Numerous studies have combined several neighborhood-level factors (typically at census tract or zipcode) to develop spatially resolved vulnerability indices with the goal of identifying populations within census tracts or zipcodes that may be most at risk for heat-related illness [27]. For example, a vulnerability index that incorporates census tract socioeconomic status was shown to be linked to higher mortality in Maricopa County, Arizona [28].

Additional physiological factors including age (65 years and above) and preexisting conditions have been found to be associated with higher rates of Emergency Department (ED)

visits and mortality due to heat-related illness. Pre-existing conditions, such as cardiovascular diseases, respiratory diseases, renal disease, diabetes, *etc.*, may limit the ability of the body to cool down by increasing blood flow to the skin and sweating, which heavily rely on the cardiovascular system, and endocrine, urinary, and integumentary processes [5, 9, 29-34]. Additionally, evidence shows that some medications (*e.g.*, antihypertensive, anticholinergic, and antipsychotic drugs) can change the temperature regulatory responses or decrease the sensory perception of environmental heat [9, 35, 36].

In Chapter 2-4, we enrolled residents in Alabama, US to examine their individually experienced heat index exposure, accounting for self-reported socioeconomic status, health conditions, and behaviors. Our participants all self-identified as Black or African American. They were from socioeconomically disadvantaged census tracts (defined by education and median annual household income using census data) and frequently experience extreme heat in the summer due to the subtropical climate. The exploration of their heat index exposure will allow more accurate exposure assessment and characterization, which may help future intervention development tailored to local needs.

Outdoor workers such as construction workers, farmers and miners face higher risk of overexposure to heat due to the non-climate-controlled work environment. The National Institute for Occupational Safety and Health (NIOSH) estimates that about 10 million workers have exposures to occupational weather-related heat (not man-made) in the US [37]. NIOSH and Occupational Safety and Health Administration (OSHA) use the maximum combination of environmental heat and metabolic heat to make work-rest schedule recommendations for outdoor workers [37, 38]. Regional weather station may inaccurately estimate the heat experienced by outdoor workers because weather station conditions can be different from specific workplaces.

Additionally, metabolic heat generated through work tasks are rarely individualized based on each worker's characteristics (e.g., age, fitness, weight) [38]. Therefore, in Chapter 2, I explored whether outdoor workers were exposed to extreme heat at the occupational setting using wearable thermometers and metabolic heat estimated from work tasks.

1.4 Heat exposure estimates via wearable sensors are feasible in providing individual level heat assessment in indoor and outdoor locations

Affordable wearable sensors providing continuous and accurate temperature and/or humidity measurements make it feasible to track individually experienced heat exposure in a group simultaneously. The study by Bernhard *et al.* (2015) reported that it was feasible to measure individually experienced temperature through sensors clipped on the shoe in both urban and rural locations in Alabama, US [39]. Other studies used similar sensors to characterize temperature exposure, with the sensor worn around the neck or on the waist [40, 41] or attached to a shirt pocket, belt or bag [42, 43]. Differences in temperature exposure across a study area and differences between individually experienced temperature and temperature measured at regional weather station have been reported [39, 41, 42, 44]. Weather station overall overestimated the daily mean temperature experienced by participants likely due to time spent in climate-controlled indoor environments, however underestimated the daily maximum temperature experienced by participants [39]. Evidence suggests that even small variations within people's microenvironment can significantly impact their overall heat exposure [34, 45]. Neighborhood level heat assessment, which provides a finer scale exposure estimation than weather station, has not been used to explain and predict individually experienced temperature or humidity. In Chapter 3-4, a total of 177 participants wore a thermometer on their shoe for seven days to measure their individually experienced heat exposure. Neighborhood

thermometers/hygrometers were deployed close to their residence to provide a finer scale of microclimate measurement in addition to regional weather station.

1.5 Urban-rural differences in exposure to heat

"Urban heat island" describes the temperature gradient of 2-10°C (3.6-19.2°F) between an urban area and its surrounding rural land [46]. Urban areas absorb more heat by paved surfaces and buildings, low vegetation coverage, reduced airflow among buildings, and heat emission from buildings and vehicles [46, 47]. Disrupted nocturnal cooling bring increased temperature at night, increasing heat-related mortality [5, 46, 48]. Globally, more than half of the population live in urban areas, and more people are expected to move into cities with rapid urbanization. The high density of vulnerable populations residing in urban environments leads to the observation that "*Urban heat waves are among the deadliest of all weather emergencies*" [49, 50]. Regional weather stations provide important meteorological data in heat-health studies, and researchers conduct more research in urban areas as study locations because urban residents are closer to a given weather station. However, heat vulnerability is not only determined by outdoor ambient heat. Since rural residents are often associated with greater sensitivity (*e.g.*, worse baseline health conditions, more people living under poverty line) and more limited adaptive capacity (*e.g.*, no/limited access to health care, no/limited access to air conditioning) compared to urban residents, their heat vulnerability may be higher [50].

Much less is known about heat-related health risks in rural areas. However, by reviewing studies on heat-related mortality in rural and urban settings published in 2000-2017, the study by Li *et al.* (2017) estimated that the relative risk of heat-related mortality in rural settings was about 3.3% larger compared to that in urban settings, suggesting heat vulnerability may be similar or even greater among rural residents compared to urban residents [50, 51]. Gabriel *et al.*

(2011) found that the mortality rates were 67.2% higher in extreme heatwaves in both the Berlin city and the rural areas around Brandenburg in 1990-2006 [52]. A few recent studies found that greater or similar vulnerability to heat was found in rural areas in both developing and developed countries [53-58]. In Chapter 3-4, we equally enrolled urban and rural participants simultaneously under the same climate conditions within a southern US state, aiming to reveal the challenges and opportunities of considering urban and rural environments in heat exposure assessment.

1.6 Encouraging even a small amount of additional time spent outdoors could increase physical activity in summer, and individual level heat exposure may be useful in determining if heat exposure increases with additional time spent outdoors

According to Healthy People 2010, only one in three adults meet the recommended amount of physical exercise every week [59]. There is evidence that the humid tropical climate may be one of the strongest deterrents against physical exercise in the US, reducing the proportion of adults meeting physical exercise recommendations by about 20% [60]. Results from analysis of the Behavioral Risk Factor Surveillance System (BRFSS) surveys suggest that adults in the Southeastern US had the highest prevalence of 28% in physical inactivity [61]. Different types of interventions (*e.g.*, one-to-one counselling, self-directed physical activity, supervised physical activity *etc.*) have been conducted to promote physical activity [62-65]. In a review study examining 150 papers, Hillsdon *et al.* (2005) found that physical activity interventions had a moderate impact on participants' self-reported physical activity; however, the effectiveness of the intervention in promoting physical activity varies among studies [66]. New procedures are needed to meet perceived convenience, accessibility, and safety requirements in a humid subtropical and tropical conditions [60].

Existing evidence suggests that moderate and vigorous exercise is positively correlated with the time spent outdoors in children and adults [67-69]. In addition, Zimmerman *et al.* (2009) suggested the use of anchors such as social norms, habits and a cultural frame to influence people's preferences for action to promote physical activity [70]. Anchoring is a cognitive phenomenon that people tend to make decisions based on the first piece of information they receive [71]. Nudging, which "alters people's behavior in a predictable way without forbidding any option [72]", has been identified as an effective approach to promote physical activity [73]. Encouraging people to spend a small amount of additional time outdoors may increase physical activity via nudging. In Chapter 4, we examined the intervention effect of spending an additional 30 minutes outdoors on physical activity and individually experienced heat index exposure in summer among 177 participants. The first piece of information participants received is "outdoor time" rather than "physical activity". Spending time outdoors may be easier to comply with, and this anchor may influence participants compliance behaviors in the intervention. Participants were not required to perform physical activity and they were free to choose what to do during the extra outdoor time. While the intervention was performed in summer, measuring individually experienced heat index exposure before and during the intervention provides important information on participants' heat exposure and heat safety. It is also an important application of individually experienced heat index exposure research.

1.7 Concurrent challenge from extreme heat and COVID-19 pandemic and high profiles of police brutality cases

The ongoing coronavirus disease 2019 (COVID-19) pandemic may lead to increased risk of heat-related illness as risk mitigation strategies before the COVID-19 pandemic – cooling centers, public outdoor recreational areas (*e.g.*, swimming pools, lakes, water parks) – may be less used due to closures and the perception of increased risk of contracting COVID-19 [74].

Conversely, COVID-19 risk mitigation strategies may bring unintended consequences to people vulnerable to heat. Medical personnel wearing Personal Protective Equipment in outdoor environments for long periods of time may have significantly lower heat exchange between their body and the environment, increasing the risk of heat-related illness [75-77]. Although staying at home may reduce the risk of contracting COVID-19, the lack of at-home air conditioning, high electricity bills or heat-related electrical blackouts may hinder people from staying cool at home in hot weather [74, 78]. Loss of jobs, increased isolation, and restricted healthcare access during the pandemic may also increase risk of heat-related illness [74, 76, 78-81].

It is unclear how residents are balancing the risks from the COVID-19 pandemic and extreme heat. While visiting cooling centers and outdoor cooling spaces are still possible when complying with updated CDC guidelines and local mandates [82, 83], it is unclear whether/how people's intention of visiting them was different in Summer 2020 compared to previous summers. The high profiles of police brutality cases in 2020 may also have impacted the public's perception of safety when using public spaces. To help people stay cool at home, low-cost and low-tech cooling options such as closing windows and blinds during the day, creating nighttime cross breeze, drinking cool water before feeling thirsty, and wearing wetted clothing are recommended [83-85]. Whether and how these at-home cooling alternatives were used differently in Summer 2020 compared to previous summers are largely unknown.

Both the COVID-19 pandemic and extreme heat disproportionately affect vulnerable and economically disadvantaged groups, including those affected by structural racism [76, 78, 86]. Persons identifying as Black or African American have 3.7 times the hospitalization rate and 2.8 times the death rate compared to persons identifying as white [87]. In Chapter 5, we conducted a

phone survey for urban and rural participants in Alabama, US to investigate whether their heat-health behaviors changed in summer 2020 due to COVID-19 compared to previous summers.

1.8 Community-engaged research offers a unique opportunity to study and address local heat health issues

This dissertation reports results from the community-engaged research through ENACT. The Centers for Disease Control and Prevention (CDC) define community-engagement as "the process of working collaboratively with and through groups of people affiliated by geographic proximity, special interest, or similar situations to address issues affecting the well-being of those people" [88]. Community-engaged research includes the full spectrum of research involving community as collaborators [89-92]. Community engaged research in environmental health includes a variety of non-academic stakeholders, such as residents in affected neighborhoods, neighborhood leaders, non-governmental agencies, and government agency representation [91]. It is designed to improve our understanding of environmental factors affecting health that may be the most promising to address based on local priorities and circumstances. Through ENACT we work on environmental health issues in Alabama with successful completion of several environmental epidemiology studies, focus groups, workshops, and phone surveys [39, 44, 93-96]. In the works in this dissertation, community partners were engaged in local environmental health problems identification, designing and implementing study plans, choosing sites for neighborhood temperature thermometers, participant recruitment, data collection instrument development and validation to ensure appropriateness for local populations, study investigation, and results dissemination back to local residents [17, 97].

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Chapter 2 Manuscript 1

Title: Estimating Occupational Heat Exposure from Personal Sampling of Public Works Employees in Birmingham, Alabama

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2.1 Abstract

Objective: This study investigated whether using thermometers clipped on workers' shoes would result in different heat exposure estimation and work-rest schedules compared to using area-level meteorological data alone.

Methods: Alabama workers (N=51) were individually monitored using thermometers on shoes. Wet Bulb Globe Temperature(WBGT) was estimated using thermometer temperatures(WBGT(personal)) or nearby weather station temperatures(WBGT(WS)). Work-rest schedules were determined from WBGT, clothing, and hourly metabolic rates estimated from self-reported tasks and bodyweight.

Results: The percent of hours exceeding the threshold limit value (TLV) were estimated at 47.8% using WBGT(personal) versus 42.1% using WBGT(WS). For work-rest recommendations, more hours fell into the most protective schedule (0-15min work/45-60min rest) using WBGT(personal) versus WBGT(WS) (17.4% vs. 14.4%).

Conclusions: Temperatures from wearable thermometers, together with meteorological data, can serve as an additional method to identify occupational heat stress exposure and recommend work/rest schedules.

Keywords: occupational heat stress, outdoor workers, heat-related illness, temperature, wet bulb globe temperature, exposure, work/rest schedules, TLV

2.2 Introduction

Occupational heat stress puts workers at risk for illnesses such as heat stroke, heat exhaustion, heat cramps, or heat rashes. According to the Bureau of Labor Statistics, overexposure to heat caused 783 deaths and 69,374 serious injuries among US workers between 1992 and 2016 [1]. Most of the heat-related deaths and illnesses can be avoided by simply identifying the risks and taking appropriate precautions [2]. In 2016, The National Institute for Occupational Safety and Health (NIOSH) published the *Criteria for a Recommended Standard: Occupational Exposure to Heat and Hot Environments*, which provides detailed guidance for preventing heat-related illnesses and injuries [3]. To implement NIOSH's heat stress criteria and initiate robust protective measurements for workers, accurate exposure assessment is required.

Core body temperature measurement is a direct indicator of risk for heat-related illnesses (HRIs). However, the existing core body temperature measurement methods, including oral, rectal, and esophageal temperatures, suffer shortcomings including inaccuracy, invasiveness, inconvenience, and cost [4]. Intestinal temperature via wireless disposable ingestible thermometers (*e.g.*, CorTemp Sensor) has been shown to be an acceptable surrogate of core body temperature[4], and these ingestible thermometers have been used to collect continuous and real-time data in recent occupational epidemiology studies [5, 6]. Its limitations include potential measurement disturbance by hot/cold beverage consumption, requirement of a costly separate data recorder, and varied measuring time before being excreted from the body [5]. Moreover, it is not practical to measure core body temperature continuously in a large number of workers who may be at risk of overheating. Therefore, improving methods using environmental conditions to estimate personal heat exposure is needed.

The Threshold Limit Value (TLV) is the ambient Wet Bulb Globe Temperature (WBGT) at which there is a heat hazard present for an acclimatized worker who has already physiologically adapted to a hot environment through repeated exposures [7]. Once TLV is reached, controls are needed to prevent heat-related diseases, whether through environmental factors or workload. Controls include work-rest schedules, shade, and hydration [7]. The WBGT index is calculated from air temperature, black globe temperature/solar radiation, dew point temperature/relative humidity, and wind speed [8, 9]. All these meteorological data influence heat exposure or the ability of the human body to dissipate heat through sweat evaporation [2, 10].The combination of WBGT, work clothing, and estimated internal generation of heat

(metabolic rate) based on the strenuousness of the work task is commonly used to recommend an hourly work-rest schedule to protect workers from HRIs [3, 7].

While current practices use area-level meteorological data to estimate occupational heat stress exposure, these estimates likely do not reflect the actual exposure experienced by workers. Urban workplace conditions can be significantly different from nearby weather stations [8]. It is possible that outdoor workers would move between indoor and outdoor environments, and outdoor workers may move through different neighborhood level microclimates while at work, which would not be captured by a stationary weather station. We hypothesized that thermometers co-located with workers will result in different estimates of heat exposure. To test this hypothesis, we first calculated differences in person-work hours above the TLV using temperature measurements either from thermometers co-located with outdoor workers or the nearest weather station to the workplace. Next, we calculated differences in the recommended work-rest schedules based on the estimated WBGT index from the nearest weather station or thermometers co-located with workers.

2.3 Methods

2.3.1. Study populations

Participants (N=21 in 2012 and N=32 in 2017) were recruited by community partner organization Friends of West End via flyers, handouts, and word of mouth at their employment locations, City of Birmingham Parks and Recreation Department, Birmingham, AL. Their typical work schedule was 6 am to 2 pm local time, Monday to Friday, performing general landscape maintenance, such as cutting grass, weeding, and planting. Potential participants filled out a screening questionnaire and were invited to come to a recruitment session if they met the screening criteria. Exclusion criteria included having medical conditions or taking medication that could prevent them from spending time outdoors or being out of town or on vacation during the study period. Potential participants attended an informational enrollment session, provided written consent, and filled out demographic and employment questionnaires. Height and weight were collected using a Befour Inc. Model # PS660 scale and a fold-up height stick and body composition measurements were collected using a Tanita BC-553 portable body composition scale. Participants in 2012 recorded their hourly tasks with the specification of indoors or outdoors in a daily log. Participants in 2017 were asked to record outdoor activities that were

over 30 minutes. The protocol for the 2012 or 2017 study was reviewed and approved by the Institutional Review Boards at the Virginia Tech and University of Alabama at Birmingham, respectively (IRB Protocol #120513012 and Protocol #15-761).

2.3.2. Temperature measurement from thermometers co-located with participants

Each participant was instructed to clip a small thermometer to one of his or her shoes for the duration of the 7-day study period. In 2012, HOBO Pendant # UA-002-64 temperature/light data loggers were used. These monitors recorded temperature readings every one minute for seven days, 24 hours a day. The HOBO Pendant monitor records temperatures ranging from 0° to 50°C with an accuracy of ±0.53°C [11]. The solar radiation shield was off for all participants in 2012 to capture light intensity measurements. In 2017, iButton devices (model# DS1922L) were clipped facing down to avoid direct sunlight. iButton is a computer chip enclosed in a 16mm thick stainless steel can. The recording interval was every five minutes. iButton DS1922L has a temperature resolution of ±0.5°C from -10°C to +65°C with an operating temperature range from -40°C to +85°C [12]. At turn-in sessions, data from HOBO Pendant and iButton sensors were downloaded and a printout of individual results was given to participants. Data were stored on password-protected computers for subsequent analysis.

2.3.3. Meteorological data:

The Birmingham International Airport Weather Station is the closest weather station to the workplace of participants. Meteorological data, including air temperature, dew point temperature, and wind speed were collected from this weather station from the National Climate Data Center Surface Data, Hourly Global dataset (DS3505) (http://cdo.ncdc.noaa.gov). Hourly averaged solar radiation was collected from GIOVANNI database at NASA (https://giovanni.gsfc.nasa.gov).

2.3.4. Data analysis

2.3.4.1. Data organization and inclusion/exclusion

Because this analysis focuses on occupational heat exposure, only data collected during work hours (between 6 am and 2 pm), Monday to Friday were included. For the 21 HOBO Pendant devices in 2012, one data logger was lost, and another was not readable upon return, leaving 19 devices intact with temperature data. Three 2012 participants (out of a total of 21) had

one day off between Monday and Friday individually, and temperature data on these three days were excluded. Additionally, three participants in 2012 worked on a Saturday, and data on these three days were included.

To address the possibility that solar radiation may increase temperatures measured from thermometers clipped to participants' shoes in certain positions and points in time when they were outdoors, upper outliers were identified in the 5-minute interval temperature measurements using median absolute deviation [13] and removed in subsequent analyses (413 out of 8,028 in 2012 and 559 out of 13,824 in 2017). The remaining 20,880 temperature measurements were hourly averaged for WBGT index calculation. Analyses with outliers intact were performed and presented in Appendices.

2.3.4.2. Calculating WBGT index

The calculation of outdoor WBGT is [3]:

$$WBGT_{outdoor} = 0.7T_{nwb} + 0.2T_g + 0.1T_a$$

where T_a = air temperature, T_{nwb} = natural wet bulb temperature, T_g = globe thermometer temperature. Because T_g measurement requires special equipment which is not used at weather stations, we used the method of Liljegren *et al.* (2008) to estimate T_g for outdoor WBGT estimations[14]. A $WBGT_{outdoor}$ (WS) index for each person-work hour was calculated from meteorological data collected at the Birmingham International Airport weather station (WS) including air temperature, dew point temperature, wind speed from the weather station and hourly averaged solar radiation from NASA. This was compared to a $WBGT_{outdoor}$ (personal) index calculated using air temperatures recorded from thermometers clipped to participants' shoes and all other variables from the weather station. Since the WBGT index calculation method used in this study requires the ambient air temperature to be greater than dew point temperature, 23 (2012 data) and 27 (2017 data) person-work hours were excluded from analysis. Weather station temperatures from the same hours were also excluded since our main goal is to compare WBGT(personal) and WBGT(WS) in the same time range. Therefore, temperatures from 813 (2012) and 1122 (2017) person-work hours were used in the final analysis.

The same amount of hourly solar radiation was applied in the $WBGT_{outdoor}$(personal) as for $WBGT_{outdoor}$ (WS) for same person-work hour. To examine the effect of the integration of solar radiation into personally measured temperature, WBGT(personal-no solar addition) was

calculated, where solar radiation was set to a default value of -99 W/m^2, i.e., no solar radiation was added into WBGT calculation, and the black globe temperature was equal to the temperature measured by thermometers co-located with participants. All participants were assumed to be wearing ordinary work clothes during the data collection period, and the clothing adjustment factor for WBGT was 0°C [15]. The WBGT(WS) or WBGT(personal) discussed in this study is equal to $WBGT_{effetive}$(WS) or $WBGT_{effective}$(personal), respectively.

The calculation of indoor WBGT is [3]:

$$WBGT_{indoor} = 0.7T_{nwb} + 0.3T_g$$

The method by Bernard *et al.* (1999) was used for indoor WBGT calculation [16]. A $WBGT_{indoor}$(WS) was calculated from air temperature, dew point temperature collected at the Birmingham International Airport weather station, and a fixed wind speed of 1m/s. The 1m/s wind speed indoor was based on the assumption that body movement indoors generates air flow over the skin so that "wind speed" on the skin would never be zero [9]. This was compared to a $WBGT_{indoor}$(personal) index calculated using air temperatures from thermometers clipped to participants' shoes. The Excel Heat Stress Calculator based on these two methods was used from the Climate CHIP website (http://www.climatechip.org/excel-wbgt-calculator). $WBGT_{outdoor}$(WS) and $WBGT_{indoor}$(WS), $WBGT_{outdoor}$(personal) and $WBGT_{indoor}$(personal) were combined as WBGT(WS) and WBGT(personal), respectively.

2.3.4.3. Calculating weight adjusted heat stress TLV with estimated metabolic rates

A decision tree was created and used to replace missing data and process conflicting data in the self-reported hourly tasks reported in daily logs from 2012 participants (see Appendix Figure 1). An hourly metabolic rate for each person-work hour was estimated based on the self-reported tasks in 2012, the American Conference of Governmental Industrial Hygienists (ACGIH) metabolic rate scale (see Appendix Table 1) [7, 17] and the General Physical Activities Defined by the Level of Intensity documentation by CDC [17]. Since there were no hourly logs from participants in 2017, their tasks during work hours were estimated as similar to the tasks performed in 2012. For better comparability between study years, each participant in 2017 was matched to a randomly selected participant in 2012 and adopted the standard human (a representative human with a body weight of 70 kg and a body surface area of 1.8 m^2. Both males and females adapt well to heat exposure, and there are no significant differences between the

sexes due to similar physiological capacity to tolerate heat [3]) metabolic rates (see Appendix Table 1) and indoor/outdoor conditions from the matched participant on a weekday-match basis.

Metabolic rates were further individually adjusted by multiplying the ratio of the worker's body weight to 70 kg (154 lbs.) of a standard human to determine the weight adjusted metabolic rate [7]:

$$Weight\ adjusted\ metabolic\ rate = \frac{Standard\ human\ metabolic\ rate(Watts) \times Worker\ bodyweight}{70kg(154lbs)}$$

A weight adjusted heat stress threshold limit value was calculated using the formula [3]:

$$\text{Weight adjusted TLV} = 56.7 - 11.5 \times \text{Log10(Weight adjusted metabolic rate)}$$

2.3.4.4. WBGT index exceedances of ACGIH TLV for each person-work hour

Whether WBGT(WS) and WBGT(personal) index exceeded the ACGIH TLV for each person-work hour was determined. If the WBGT index exceeds ACGIH TLV in a given person-work hour, it suggests risk of overexposure in that given hour and a work-rest schedule should be implemented to decrease the risk of HRIs [3, 7]. Since different temperature sensors (HOBO Pendant versus iButton) were used in 2012 and 2017, and the gender ratio in the two study periods were different, the number of person-work hours that the WBGT index exceeded TLV in 2012 and 2017 were also analyzed separately and results are shown in Appendices.

2.3.4.5. Recommending hourly work-rest schedules based on WBGT index

Participants in this study were considered acclimatized workers [18] for the purposes of this analysis. Recommended exposure limits (RELs) and recommended work-rest cycles were determined for each person-hour by using either WBGT(WS) and WBGT(personal) indices, based on the criteria by NIOSH, CDC [3] and Bernard's heat stress screening evaluation document [19]. Participants were approximated to a "standard human" of 1.8 m^2 body surface when determining RELs. Weight adjusted metabolic rates were assigned into different levels of work to use the screening criteria of TLV to determine work-rest recommendations(see Appendix Table 1).

2.4 Results

2.4.1. Participant demographic characteristics and estimated metabolic rate based on work tasks

Characteristics of the study population are shown in Table 2-1. The age median(range) was 44(24, 57) in 2012 and 39.5(21, 60) in 2017. In 2012, 84% of participants were male while all participants were female in 2017. The median(range) Body Mass Index (BMI) was 36.1(25.7, 36.6) among females in 2012 and 29.2(18.3, 38.4) among males in 2012. In 2017, the median(range) BMI among all female participants was 34.3(19.3, 52.3). Most of the participants were African American (89% in 2012 and 94% in 2017).

2.4.2. Estimated metabolic rates

The average of estimated hourly metabolic rates of "standard human" during work hours was 252.9 ± 76.1 (mean ± SD) Watts for participants in 2012 and 253.4 ± 74.9 (mean ± SD) Watts in 2017. The average of estimated hourly weight adjusted metabolic rate was 327.1 ± 129.3 (mean ± SD) Watts for participants in 2012 and 330.0 ± 132.0 (mean ± SD) Watts in 2017. Estimated hourly metabolic rates or weight adjusted metabolic rates were not statistically different between 2012 and 2017 (P-value = 0.88 or 0.63, respectively).

2.4.3. Environmental conditions during 2012 and 2017 study periods

Temperatures from thermometers clipped to participants' shoes had a wider range compared with temperatures recorded at the nearest weather station (see Figure 2-1). The daily hour maximum and average temperature during work hours (6 am to 2 pm) were 35.0℃ and 28.1 ± 3.5℃ in 2012, and 32.2℃ and 27.9 ± 2.8℃ in 2017, respectively. The average WBGT(WS) during person-work hours was significantly lower in 2012 compared to 2017 (27.1 ± 3.3℃ vs. 28.0 ± 4.0℃, P-value < 0.001).

2.4.4. Person-work hours exceeding TLV

On average, WBGT(personal) was higher than WBGT(WS) for all the person-work hours in 2012 (27.5 ± 3.4℃ (mean ± SD) vs. 27.1 ± 3.3℃, P-value=0.003) and 2017 (28.6 ± 3.9℃ vs. 28.0 ± 4.0℃, P-value=0.0007), respectively. The 2012 and 2017 datasets were initially analyzed separately, and the trends of the results of person-work hours that exceeds TLV were similar (see Appendix Figure 2, Appendix Figure 3). Therefore, results from 2012 and 2017 were combined and presented as one overall dataset. Of the total 1,935 person-work hours analyzed,

WBGT(personal) estimated 47.8% person-work hours exceeded TLV while WBGT(WS) estimated 42.1% exceeded TLV. Percentages of person-work hours of WBGT that exceeds weight adjusted TLV were calculated for each participant. On average, WBGT(personal) estimated more hours exceeded TLV at 7 am~11 am and 1 pm~2 pm than WBGT(WS) across all participants. There was a significant difference (P-value =2.08E-05) in the percentages between WBGT(personal) and WBGT(WS) at 7am but not at other hours(see Figure 2-2).

Hourly recommended work-rest schedules for each participant were determined using WBGT(personal) or WBGT(WS), and a percentage of person-work hours for each work-rest schedule was calculated (see Figure 2-3). Across all participants, using WBGT(personal) estimated more person-work hours in the 45~60 min work/0~15 min rest, 30~45 min work/15~30 min rest,15~30 min work/30~45 min rest, 0~15 min work/45~60 min rest hourly schedule compared to using WBGT(WS), but the differences were not significant (P-value >0.05). Using WBGT(personal) estimated 17.4% of all person-work hours fall into the 0~15 min work/45~60 min rest schedule, which is recommended in the highest HRI risk conditions, while WBGT(WS) only estimated 14.4% of person-work hours fall into this high-risk category. We found that WBGT index sometimes exceeded TLV even when participants were at rest with an estimated hourly metabolic rate around 115 Watts. These person-work hours fell into the Caution category since no further work-rest schedule could be recommended. WBGT(personal) estimated 1.0% of all person-work hours were in the Caution category while WBGT(WS) estimated 0.8% hours (see Figure 2-3). All other person-work hours (55.8% ± 2.3% for WBGT(personal) and 60.9% ± 2.4% for WBGT(WS)(P-value=0.23)) did not fall into an HRI risk category, allowing for continuous work.

2.5 Discussion

The primary goal for this study was to determine whether the use of a WBGT(personal) index would result in different HRI risk estimates from occupational heat exposure when compared to a WBGT(WS) index. For the same person-work hour, the difference between WBGT(personal) and WBGT(WS) is due to the different temperature measurement from thermometers or weather station, which explains the differences in person-work hours above TLV and different work/rest schedule recommendations. WBGT(personal) estimated that more person-work hours fell into all protective schedule categories than WBGT(WS), indicating using WBGT(personal) may provide more protection for workers from HRIs. If only WBGT(WS) was

used, longer work versus rest periods would be recommended, which may result in placing workers at a higher risk of HRIs. While a recent study concluded regional weather station data provides accurate estimates of worksite heat index when compared to individually experienced temperature and humidity [20], our study suggests additional relatively simple calculations to estimate WBGT using individually experienced temperature, tasks performed, and worker's weight may improve work-rest schedule estimation.

The Universal Thermal Climate Index (UTCI) is an alternative, regression-based metric based on the heat balance mechanism of the human body using the same input variables as WBGT. Since UTCI does not consider metabolic rate, clothing impact, or body movement during real work situations, the WBGT index is considered more comprehensive [14, 21]. The Predicted Heat Strain (PHS), which is "based on analysis of body heat balance and the required sweat rate for the maintenance of a stable core temperature", is used to calculate the recommended exposure time independent of meteorological conditions [22]. However, it has been demonstrated that the WBGT index provides a more conservative assessment that allows shorter exposure times [23]. An empirical short-term safe exposure time model was proposed using the WBGT index, metabolic rate, and clothing by Bernard *et al.* in 2009 [24]. The model was derived from the metabolic rate of 380W, but not validated against other data [25]. Therefore, the Recommended Exposure Limits (RELs) from NIOSH were used to recommend work/rest schedules in this study.

Limitations of this study include a relatively small sample size; therefore results in this study may not be generalizable to other urban outdoor workers in other locations and gender effects, if any, would be difficult to detect in the current study (see Appendix Figure 4, Appendix Figure 5). Second, the participants' metabolic rates were estimated using the hourly self-reported tasks in the daily log in 2012. It is possible that the reported task did not occupy the whole hour for each participant and application of 2012 tasks to the 2017 participants limits our ability to incorporate potential variability in tasks performed. The work tasks performed by 2012 participants were randomly matched to participants in 2017 on a weekday basis (*e.g.*, Monday to Monday, Tuesday to Tuesday). Female workers might be assigned to lighter workload tasks. However, we found that in 2012 female participants (N=3) on average had higher metabolic rates compared to male participants (N=16) (263.4 vs. 250.7 Watts). The small number of female participants prevented the deduction that female workers also performed higher workload tasks

in 2017. Participants with higher individual income might be assigned with more tasks with lower metabolic rates (*e.g.*, more paperwork, giving training to entry level workers). We only have annual household income instead of individual annual income, which prevented us from matching tasks by income. Older participants might be senior workers who were more experienced and more likely to be assigned to tasks with a lighter workload. Therefore, we randomly matched a participant in 2017 to a participant in 2012 whose age was in the range of -/+ 3 years the age of a participant in 2017. For example, a participant in 2017 age 25 was randomly matched to a participant who was 22-28 years old in 2012. The matching tasks by age groups resulted in similar estimated mean metabolic rates compared to the main results (260.5 vs. 263.4, student's t-test p-value 0.23). Weight-adjusted metabolic rates were assigned based on the task category without the consideration of all individual differences, including age, basal metabolic rates, and other body measurements. Future research could incorporate biometrics (i.e. heart rate monitors) to further evaluate the effect of individual differences in metabolic rate.

Different thermometers co-located with participants were used in the 2012 and 2017 periods of this research. Prior to the 2017 data collection, we tested the temperature measurement precision of three iButton and six HOBO Pendant devices placed at the same indoor location for 32 consecutive hours. We found that iButton had better precision than HOBO Pendant devices, which lead us to use iButton in 2017.

The placement of thermometers on the worker (neck or waist) has been previously shown to affect temperature readings [20], with placement at the waist more accurately capturing mean workplace heat index estimated from regional environmental monitoring data. Our placement on the shoe may have also affected the temperature measurements due to proximity to the ground and depending on the type of surface the participant was on (*e.g.* grass versus pavement); however, the shoe position was chosen based on pilot trials that suggested thermometers attached to other articles of clothing picked up body heat and preference for the shoe position in terms of comfort and discreteness.

Additionally, the impact of solar radiation on temperature measurements from thermometers co-located with participants should be considered in future studies, as also suggested by Mac *et al.* (2018) [20]. Since the HOBO Pendant devices measured temperature without a solar radiation shield and iButton devices were worn facing down, the amount of solar radiation captured by these devices cannot be quantified at this time. In a sensitivity analysis, the

impact of additional solar radiation not captured by HOBO Pendant and iButton devices was simplified as negligible (no additional solar radiation) in the $WBGT_{outdoor}$(personal) calculation. In this analysis, 16.0% of all person-work hours of WBGT(personal-no solar addition) were estimated to exceed TLV compared with 47.8% of WBGT(personal). There are significant differences (P-value < 0.001) in the average percentage of person-work hours above TLV by using WBGT(personal) or WBGT(personal-no solar addition) at 7 am~2 pm (see Appendix Figure 6). WBGT(personal) recommended more hours than WBGT(personal-no solar addition) in all work/rest regimens (see Appendix Figure 7). While WBGT(personal-no solar addition) is useful to provide a higher bound on the impact of solar radiation possibly captured by the devices, the true value is likely less. Additionally, upper outliers from personal thermometer temperature measurements were removed to address the concern that solar radiation captured by devices elevated personal air temperatures temporarily. There was a minimal effect of upper outlier removal (see Appendix Figure 8, Appendix Figure 9). In the future, development of small, wearable thermometers equipped with a solar radiation shield or co-location of a black globe thermometer with participants, which combines the effects of air temperature and solar radiation, could be used to assess solar radiation effects more accurately.

This study suggests consideration of microclimates for outdoor workplaces may result in more precise work-rest schedule recommendations. While the work-rest regimen recommendations in this study were based on post-incidence heat stress estimation and did not provide real-time feedback, employers and workers can still benefit from the results by considering more workplace specific and personal risk factors to prevent HRIs. Additionally, employers could collect real-time meteorological data specific to their workplace or purchase WBGT meters(*e.g.* QUESTemp QT32/34/36) to place in common work areas. These meters automatically calculate WBGT and display work-rest regimens for each of four metabolic work categories [26]. For example, the NIH Heat Stress Program monitors hourly during work hours at all official NIH facilities [27].

Placement of a WBGT meter may not be feasible at many workplaces; therefore, implementing work-rest schedules based on heat index from temperature and humidity measurements may be more realistic (*e.g.* BP U.S. Pipelines & Logistics (USPL) Safety Manual) [28]. For example, the Heat Safety Tool from OSHA, a smartphone application, reports real-time data from the nearest weather station based on the GPS location of the phone. This

information can then be used to develop industry specific work-rest schedules [28]. However, as detailed in this paper, NIOSH recommends an approach that includes solar radiation and wind speed, in addition to temperature and humidity, to determine work-rest schedules [3].

Workers could also receive training on adjusting the rest time with consideration of their personal risk factors including age, weight, physical fitness, water intake, medical conditions, and medications, *etc.* To minimize work-rest scheduling effects on productivity, work hours could be adjusted to allow performance of strenuous outdoor work in the early morning hours. Also, sedentary tasks (*e.g.* meetings, paperwork) could be scheduled during rest periods.

Beyond implementation of the more specific work-rest scheduling, engineering controls like installing a form of shade on all mowers to prevent direct radiant heat and UV damage to the skin can be implemented. Cooling stations and personal protective equipment (PPE), such as cooling vests, could be made available for use along with training on proper use. During heat wave days, a daily weigh in and out can be implemented to ensure workers are not losing a dangerous amount of water. Frequent water breaks could be encouraged as part of a hydration protocol.

2.6 Conclusion

Temperature measurements from thermometers co-located with participants had a wider range than those collected from the nearest weather station. More person-work hours of WBGT(personal) exceeded ACGIH TLV than when using WBGT(WS) to calculate exceedances (47.8% vs. 42.1%). By using WBGT(personal), more person-work hours fell into the 0~15 min work/45~60 min rest hourly schedules (17.4% vs. 14.4%), indicating conditions with the highest risk of HRI. Our findings suggested that using temperature measured by small thermometers clipped to outdoor workers' shoes, together with meteorological data, can serve as a method to identify occupational heat exposure and recommend more protective work/rest scheduling.

Table 2-1 Demographics and body mass index for participants in 2012 and 2017

Parameters	Year 2012	Year 2017
Participant number	19	32
Median age (range), years	44(24-57)	39.5(21-60)
Sex-Male	16(84%)	0(0%)
Sex-Female	3(16%)	32(100%)
% Black or African American	17(89%)	30(94%)
Education		
Less than High School Diploma	4(21%)	2(6%)
High School Diploma (or GED or Equivalence)	8(42%)	16(50%)
Post-Secondary Certificate and above	7(37%)	14(44%)
Income		
Less than $20,000	4(21%)	10(31%)
$20,000 to $49,999	11(58%)	18(56%)
$50,000 and above	4(21%)	4(12%)
Body Mass Index(BMI)		
BMI in Female (Median, range)	36.1(25.7-36.6)	34.3(19.3-52.3)
BMI in Male (Median, range)	29.2(18.3-38.4)	N/A
Obese (BMI ≥30.0)	9(47%)	22(69%)

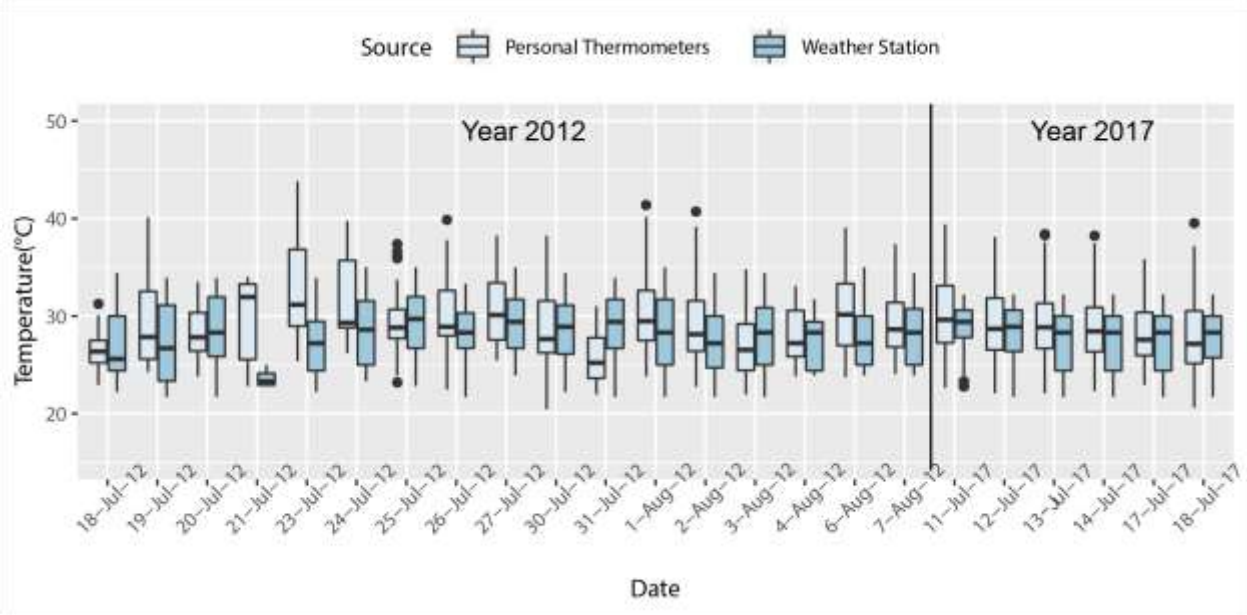

Figure 2-1 Comparison of hourly temperature measurements from personal thermometers and from weather station between 6 am and 2 pm on the days participants worked. Minimal and maximal, 25th and 75th percentiles, median (solid line in the box), and outliers (black circle) were shown.

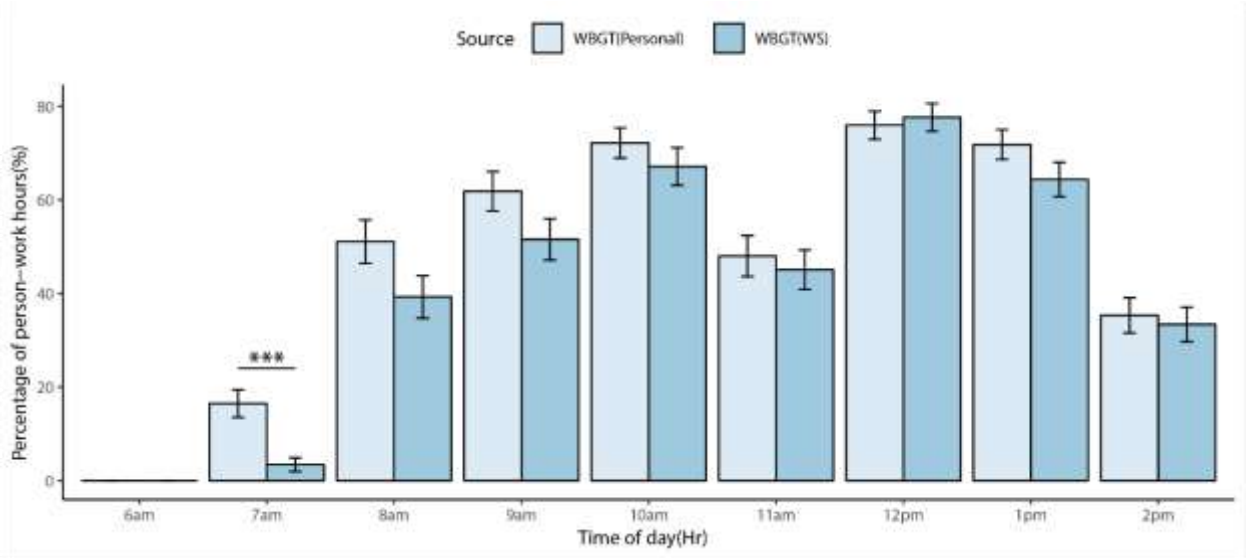

Figure 2-2 Average percentage of person-work hours of WBGT index that exceeds weight adjusted TLV across all participants(Mean ± Standard Error).Statistical significance symbols: '***' denotes P-value of 0 - 0.001, ' ' denotes P-value >0.05 and no significant difference.

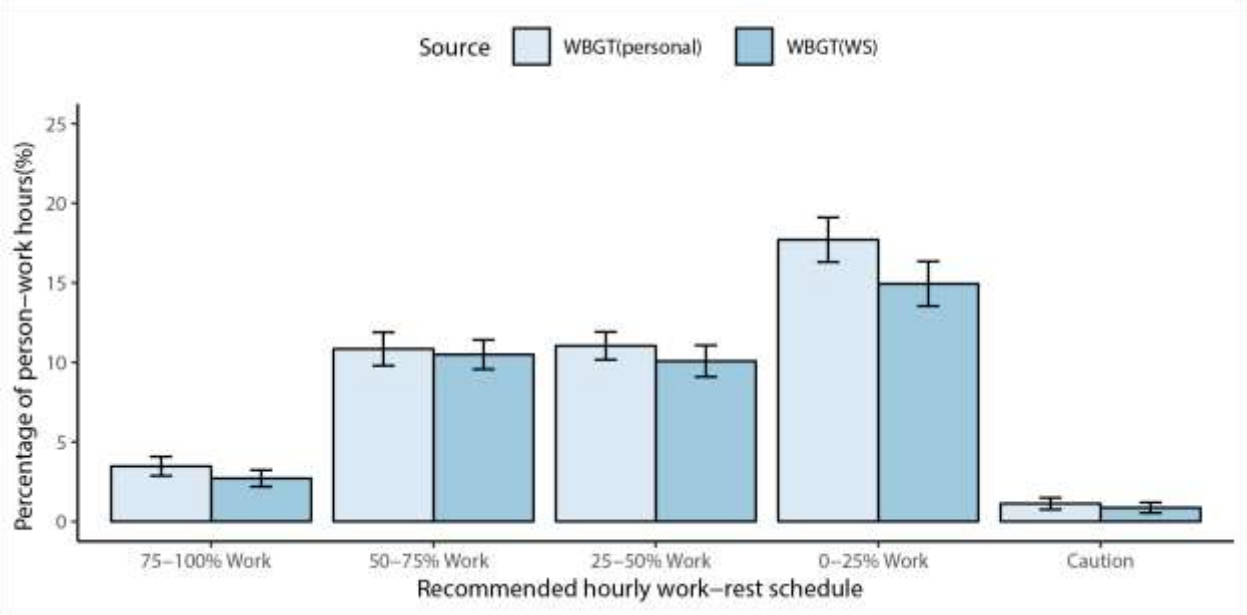

Figure 2-3 Average percentage of person-work hours in recommended work-rest schedule based on WBGT index across all participants(Mean ± Standard Error). 75-100% Work is 45-60 min work/0-15 min rest per hour, 50-75% Work is 30-45 min work/15-30 min rest per hour, 25-50% Work is 15-30 min work/30-45 min rest per hour, 0-25% Work is 0-15 min work/45-60 min rest per hour. Caution category represents WBGT index that exceeds weight adjusted TLV when participants were at rest (estimated hourly metabolic rate around 115 Watts) in that person-work hour. Unshown percentage of hours fell into continuous work category. The percentage of person-work hours in Continuous work is 55.8%±2.3% for WBGT(personal) and 60.9%±2.4% for WBGT(WS)(P-value=0.23). Statistical significance symbols: ' ' denotes P-value >0.05 and no significant difference.

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Chapter 3 Manuscript 2

Title: Characterization of Heat Index Experienced by Individuals Residing in Urban and Rural Settings

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3.1 Abstract

Heatwave warning systems rely on forecasts made for fixed-point weather stations (WS), which do not reflect variation in temperature and humidity experienced by individuals moving through indoor and outdoor locations. We examined whether neighborhood measurement improved the prediction of individually experienced heat index in addition to nearest weather station in an urban and rural location. Participants (residents of Birmingham city, Alabama [N=89] and Wilcox County, Alabama [N=88]) wore thermometers clipped to their shoe for 7 days. Shielded thermometers/hygrometers were placed outdoors within participant's neighborhoods (N=43). Nearest weather station and neighborhood thermometers were matched to participant's home address. Heat index (HI) was estimated from participant thermometer temperature and weather station humidity per person-hour (HI[individual]), or weather station temperature and humidity, or neighborhood temperature and humidity. We found that neighborhood HI improved the prediction of individually experienced HI in addition to weather station HI in the rural location, and neighborhood heat index alone served as a better predictor in the urban location, after accounting for individual-level factors. Overall, a 1°C increase in HI[neighborhood] was associated with 0.20°C [95%CI (0.19, 0.21)] increase in HI[individual]. After adjusting for ambient condition differences, we found higher HI[individual] in the rural location, and increased HI[individual] during non-rest time (5am-midnight) and on weekdays.
Keywords: exposure assessment, exposure sensors, environmental health policy

3.2 Introduction

Exposure to extreme heat is a significant public health problem. Extreme heat events increase adverse health outcomes in the United States (US) and heat-related deaths are projected to increase in the absence of effective adaptation measures with continued warming [1-3]. According to the National Weather Service (NWS) hazard statistics report, there were more heat-related fatalities in the US in 2018 than fatalities associated with other forms of weather [4]. Using death records between 2006 and 2010, 31% of weather-related deaths were attributed to excessive heat exposure in the US, and was second only to cold exposure as a coded cause of mortality [5]. Over 7,400 deaths reported from 1999 to 2010 in the U.S. were associated with exposure to excessive natural heat [6], and approximately 28,000 heat-related illness hospitalizations in 20 states were recorded from 2001 to 2010 [7].

Extreme heat warning systems rely on temperature and humidity forecasts made for fixed-point weather stations (WS) to trigger alerts and initiate response plans to reduce the human health consequences of heatwaves [8-10]. These systems typically do not take into account variations due to microclimates across a landscape, although an experimental HeatRisk forecast product developed by NWS provides finer scale heat risk guidelines for western U.S. states [11]. Additionally, these systems do not account for variations due to the activity patterns of individuals moving through indoor and outdoor environments and other factors including acclimatization, dehydration, medications, and health conditions [12]. For example, a study of U.S. football player deaths found that 100% of heat-related deaths occurred in conditions that did not trigger a National Weather Service alert [13]. As a first step to understand the importance of exposure variation in predicting risk at the population level, a more precise measurement of exposure at the individual level is needed.

Recent studies have characterized individually experienced temperature and humidity by using wearable sensors. The study by Bernhard *et al.* (2015) reported that it was feasible to measure individually experienced temperature through sensors clipped on the shoe in both urban and rural settings in Alabama (AL), US [14]. Other studies used similar sensors to characterize exposure, with the sensor worn around the neck or on the waist [15, 16], or attached to a shirt pocket, belt or bag [17, 18]. Differences in exposure across a study area and differences between individually experienced temperature and temperature measured at regional weather station have been reported [14, 16, 17, 19]. Neighborhood level heat index assessment, which provides a finer

scale exposure estimation than weather station, has not been used to explain and predict individually experienced temperature or humidity.

Studies estimating adverse health outcomes associated with extreme heat are usually undertaken in urban areas where more people are closer to a given weather station. Much less is known about heat-related health risks in rural areas. However, by reviewing studies on heat-related mortality in rural and urban settings published in 2000-2017, the study by Li *et al.* (2017) estimated that the relative risk of heat-related mortality in rural settings was about 3.3% larger compared to that in urban settings [20]. While the temperatures experienced in cities are heightened due to the urban heat island effect, persons living in rural areas typically have less access to air conditioning, longer travel time to medical help, and longer power outages during heatwave days [21, 22]. Studies characterizing heat index exposure simultaneously in urban and rural settings have been conducted only in outdoor workers, revealing significant outdoor worker variation in temperature exposures within and between the study locations [16]. Whether non-outdoor workers have different exposure in rural and urban settings is relatively unexplored.

This study investigated whether individually experienced Heat Index (HI, °C) was different in an urban vs. rural setting and evaluated how well weather station HI or neighborhood HI predicted individually experienced HI in both settings. We recruited participants with comparable characteristics in urban Birmingham, AL and in rural west central Wilcox County, AL, settings that frequently experience daytime high temperatures of 29-32°C, which are considered at least in the Caution risk by the National Weather Service assuming a relative humidity of 50% [10, 23]. This work builds from prior studies that have been conducted to characterize and predict individually experienced temperature and humidity by combining with neighborhood microclimate differences in an urban vs. rural setting, together with individual-level factors that could potentially affect vulnerability to heat stress. This study aims to improve extreme heat event response by improving the characterization of who, when, and where people are at a risk of exposure to excess heat index.

3.3 Methods

3.3.1. Participant recruitment and individual monitor deployment

In the summer of 2017, residents in Birmingham, AL (N=90) and Wilcox County, AL (N=90) were screened and recruited in partnership with Friends of West End, Birmingham AL

and West Central Alabama Community Health Improvement League, Camden AL. Sample size was determined to detect a mean difference between urban and rural exposure of 0.7°C, with a standard deviation of 1.7°C, if we assume that the average temperature in rural areas is 26.0°C based on our pilot study [14]. Eligibility criteria include women aged 19-66 and availability to participate in a one-week study between July 10-19, 2017. We recruited woman participants to reduce variability for primary exposure variables of interest and to improve the ability to recruit and follow-up with participants based on previous studies conducted by the community-academic partnership [14]. We excluded participants having medical conditions or taking medication that could prevent them from spending time outdoors or being out of town during the study period. Potential participants attended an informational enrollment session, provided written consent, and filled out demographic and employment questionnaires. We collected the height and weight of participants with a Befour Inc. Model #PS660 (Befour Inc., Wisconsin, US) scale and a fold-up height stick. We collected body composition measurements of participants with a Tanita BC-553 (Tanita Corporation of America, Inc., Illinois, US) portable body composition scale. Participants were asked to perform normal activity in the first two days and spend an additional 30 minutes outdoors beyond their normal activities on days 3-7 of participation. Participants kept a daily log of their time spent outdoors and pedometer readings, and they completed an exit survey. We made three follow-up phone calls to participants during the study to troubleshoot any challenges with compliances to wearing the monitors and filling out the daily logs. Participants received up to $150 to cover the time and travel expenses associated with participation in the study.

Each participant wore an iButton thermometer (model# DS1922L from Maxim Integrated, California, US) clipped on the shoe and a pedometer, Yamax Digi-Walker (model# SW-200 from Yamax, Texas, US), clipped at the waist. The iButton devices were clipped facing down to avoid direct sunlight. iButton is a computer chip enclosed in a 16mm thick stainless steel can, and it has a temperature resolution of ±0.5°C from -10°C to 65°C with an operating temperature range from -40°C to +85°C [24]. iButton thermometers were factory calibrated using NIST standards [24]. In previous applications we have confirmed that factory-calibrated iButtons return consistent values when tested in a common environment [25-27]. iButton thermometers were set to record temperature every five minutes. At turn-in sessions, we downloaded data from the iButton data loggers and gave a printout of individual results to each

participant. We stored all data collected on password-protected computers for subsequent analysis. Informed consent was obtained from all participants. This study is registered at clinicaltrials.gov (NCT03614780) and was approved by Virginia Tech Institutional Review Board (15-761).

3.3.2. Nearby weather station data collection and processing

We accessed meteorological data, including air temperature, relative humidity, wind speed, and location coordinates during the study period from all weather stations in AL from the National Climate Data Center Surface Data, Hourly Global dataset (DS3505) (http://cdo.ncdc.noaa.gov). We matched a nearest weather station to each participant's home address. We matched six weather stations to participant home addresses: Bessemer Airport weather station, Birmingham International Airport weather station, Craig Field weather station, Demopolis Municipal Airport weather station, Mac Crenshaw Memorial Airport weather station, and Middleton Field Airport weather station. We calculated hourly weather station heat index (HI[WS]) (°C) from hourly temperatures and relative humidity from the weather station by using "*weathermetrics"* packages in R based on the methods in Appendix Figure 10 [28].

3.3.3. Neighborhood monitor deployment

A total of 43 iButton thermometers/hygrometers (model# DS1923 from Maxim Integrated, California, US) were deployed in participants' neighborhoods in Birmingham (N=29) and in Wilcox County (N=14). Each iButton was placed in a radiation shield [25] and affixed to a tree at various locations (*e.g.*, in yards or along sidewalks). We measured the exact location coordinates of each neighborhood iButton using smartphone Global Positioning System. Neighborhood iButtons were set to measure air temperature and relative humidity hourly. We matched a nearest neighborhood monitor to each participant's home address and calculated hourly neighborhood heat index (HI[neighborhood]) (°C) from the hourly temperatures and relative humidity from neighborhood iButton data loggers based on the methods in Appendix Figure 11.

3.3.4. Participant iButton temperature measurement data processing

A total of 178 participant thermometers (89 in Birmingham and 89 in Wilcox County) had valid temperature measurements at turn-in. Thermometer temperature measurements outside each participant's study period based on check-in/check-out session time were excluded from the

analysis (decision tree presented in Appendix Figure 12). We removed upper outliers of the participant thermometer temperature to remove potential artifacts of iButton measurements. We calculated hourly individually experienced heat index, HI[individual] (°C), from participant thermometer hourly averaged temperatures and matched weather station relative humidity, based on the methods in Appendix Figure 13. To test the effects of using different sources of relative humidity in estimating HI[individual], we calculated another set of HI[individual] using neighborhood monitor relative humidity in the place of weather station relative humidity. For each person-hour of HI[individual], we matched a HI[WS] from the nearest weather station and a HI[neighborhood] from the nearest neighborhood monitor to indicate the ambient conditions. This resulted in 27,470 person-hours of HI estimates in an ***Inclusive*** dataset for following analysis.

We performed sensitivity analysis using ***Complete*** dataset in which no outliers were removed. We additionally performed sensitivity analysis using ***Restrictive1*** and ***Restrictive2*** datasets that included the data from person-days on which the participant thermometer temperature variation at 5am-midnight was greater than 1°C or 2°C, respectively. In an attempt to reduce artifacts of shoe iButton temperatures, we applied a -0.5°C bias correction to all the participants thermometer temperatures taken at 8 am-8 pm in the ***Bias Corrected*** dataset when participants were more likely to wear shoes with a thermometer clipped on in the Inclusive dataset. A sensitivity analysis was performed in the Bias Corrected dataset. The methods of obtaining these additional datasets are presented in Appendix Figure 13.

3.3.5. HI risk classification

We assigned a risk level to each person-hour based on the National Weather Service HI classification (https://www.weather.gov/ama/heatindex). A HI of 26.7°C or lower is classified as Safe, 26.7-32.2°C as Caution, 32.2-39.4°C as Extreme Caution, 39.4-51.1°C as Danger, >51.1°C as Extreme Danger. We performed a time-series analysis of the risk categories by using HI[participant], HI[neighborhood] and HI[WS].

3.3.6. Pedometer readings processing

Participants recorded their pedometer reading at night on each day without resetting the pedometer. We estimated daily steps based on the pedometer readings recorded on daily logs. Building from the previous decision tree [27], we modified it by removing invalid data based on

daily log notes from participants and replacing extreme daily steps <1,000 or ≥25,000 with NA (see Appendix Figure 14) [29, 30] and used it to further process the pedometer data adjusting for missing or unrealistic recorded data. A sensitivity study evaluated the effects of pedometer data processing methods.

3.3.7. Data analysis

We examined the diurnal pattern of daily average and max HI[individual] in different groups. Only person-days with 24 hours data were included in the daily average analysis. We performed a sensitivity analysis on individually experienced temperature in place of HI.

We fitted linear mixed models to determine factors significantly associated with HI[individual] exposures of participants. Models included a random effect term, allowing us to account for multiple measurements from a single person. The dependent variable, HI[individual], was modeled using independent variables of HI[WS] or HI[neighborhood], and covariates including age, income (≥ $20,000 vs. < $20,000 reported annual household income), education (≥ high-school diploma or equivalent vs. < high school diploma or equivalent), measured body fat (%), weekend, non-rest time (5am-midnight), hourly weather station mean wind speed (m/s), intervention, log(mean steps), employment, and rural or urban setting. Whether HI[WS] or HI[neighborhood] explained more variance in models of HI[individual] was evaluated using the Akaike information criterion (AIC) for each model. The AIC of the three models (HI[WS] and HI[neighborhood], HI[neighborhood] only, HI[WS] only) were computed and the $\Delta i = AIC_i - AIC_{min}$ were calculated. The model best estimated has the $\Delta i \equiv AIC_{min} \equiv 0$. When $\Delta i \leq 2$, there is no substantial difference between the two models and a simpler model was preferred [31]. Models were stratified by urban/rural setting and across the occupationally and non-occupationally exposed groups. Suspecting indoor air-conditioning and human activity were potential reasons for daily fluctuations in individually experienced HI, we fitted the regression models separately for non-rest time (5am-midnight) and rest time (midnight-5am). Measured body mass index (BMI) and measured body fat (%) were highly correlated, so only measured body fat (%) was added in the models [14]. Seven participants (1,062 person-hour observations) were dropped from the analysis because of missing measured body fat (%), reported annual household income and education data. We used "*lmer"* function in "lme4" package in R to run the models [32]. We performed a sensitivity analysis on the Complete dataset, Restrictive1 and Restrictive2 datasets.

3.4 Results

3.4.1. Participant demographic characteristics

Characteristics of the final study population are presented in Table 3-1 and participant enrollment and follow-up are presented in the CONSORT flow diagram in Appendix Figure 15. Participants were female and most of them identified as Black or African American. Thirty-two participants in Birmingham were outdoor workers (Urban OutWor). Urban OutWor participants were on average significantly younger than other Urban residents (p-value 0.03) and had higher mean daily steps than Urban residents (5,782 vs. 4,548 steps, p-value 0.02). The adopted pedometer processing method had a minimal effect on daily steps (see Appendix Figure 16). Urban OutWor participants on average had a lower measured body fat (%) (p-value 0.04) compared to other Urban residents. Rural residents on average had a higher measured body fat (%) (p-value = 0.04) compared to Urban residents. There was no significant difference in access to central air-conditioning at home, education level, annual household income level, BMI, and obesity prevalence between groups.

We compared the characteristics of the study participants in Birmingham and Wilcox County with the characteristics of populations residing in these two places, respectively. A higher proportion of the study participants were self-identified as African American or Black than Birmingham or Wilcox County census reports (95% vs 71% in Birmingham, 100% vs 71% in Wilcox County). The participants in this study were more highly educated (94% vs 86% high school graduates and above in Birmingham, 88% vs 77% high school graduates and above in Wilcox County), and less wealthy (59 [66%] of participants reported <$20,000 vs $35,346 median annual household income in Birmingham, 57 [65%] of participants reported <$20,000 vs $27,237 median household income in Wilcox) compared to US Census estimates [33].

3.4.2. Distances between participant residence and neighborhood iButtons/weather station

The nearest neighborhood thermometer and the nearest weather station were matched to each participant's home address (see Appendix Figure 17), and the summarized distances are shown in Table 3-2. Neighborhood monitors were significantly closer to participants than weather station in the three population groups. Rural residents were on average significantly farther away from nearby weather station compared to Urban residents (50.12 kilometers [95%CI (48.61, 51.63)] vs. 12.37 kilometers [95%CI(11.28, 13.46)] , p-value < 2.2E-16).

3.4.3. Comparison of HI from participants, neighborhood and weather station

We examined the diurnal patterns of HI[individual], HI[neighborhood] and HI[WS] over the 8 days of the study. The group average of individually experienced mean and maximum HI in the three population groups are shown in Figure 3-1 and Figure 3-2.

Among Rural residents and Urban residents in Figure 3-1, we found that the HI[WS] and the HI[neighborhood] underestimated the population-averaged HI[individual] at night (approximately 8 pm-8 am) for both mean and max HI. Max HI[WS] was similar to max HI[individual] during the day (8 am-8 pm) in Rural residents and Urban residents, respectively. HI[WS] deviated significantly less from HI[individual] than HI[neighborhood] between 10am-3pm among Rural residents in both mean and max HI. We examined the outdoor occupation effect by comparing HI[individual] in Urban residents and Urban OutWor participants. Urban OutWor participants on average had significantly higher max and mean HI[individual] during the day but similar HI[individual] at night compared to Urban residents. Both HI[WS] and HI[neighborhood] underestimated the population average max HI[individual] in Urban OutWor participants. Figure 3-2 shows that the daily mean HI[WS] and HI[neighborhood] overall overestimate the population average of HI[individual] in Rural residents and Urban residents. The daily max HI[neighborhood] estimated daily max HI[individual] better than daily max HI[WS] in all groups. Urban OutWor participants on average had a significantly lower daily mean and max HI[individual] on weekends. Analyses with temperature only, instead of estimated HI, from thermometers clipped on shoes, neighborhood monitors and weather station were performed and presented in Appendix Figure 18, Appendix Figure 19, with similar trends to those presented for HI.

The risk distribution patterns based on HI are shown in Figure 3-3. Participant thermometers, neighborhood monitors and weather station reported similar population mean frequency of person-hours (%) in the Safe exposure category. When we looked at specific unsafe exposure categories, we found that neighborhood monitors and weather station significantly underestimated the Extreme Danger category exposure in all groups and significantly underestimated the Caution category exposure in Rural residents only. Across all participants, we found that the HI[individual] estimated 1,420 out of 27,470 (5.17%) person-hours from 148 participants in Danger and Extreme Danger categories, respectively, which peaked between 1 pm-3 pm (see Appendix Figure 20). Of these 1,420 person-hours, HI[neighborhood] and HI[WS]

estimated 406 (28.59%) and 453 (31.90%) person-hours in the Safe category, respectively. When extreme values for HI[individual] at night (N=142 person-hours) were removed in sensitivity analyses, the results were consistent with the main results, with an estimated 1,312 out of 27,328 (4.80%) person-hours from 148 participants in Danger and Extreme Danger categories (see Appendix Figure 21, Appendix Figure 22, Appendix Figure 23, Appendix Figure 24).

3.4.4. Predictive value of weather station HI and neighborhood HI

A model including HI[neighborhood], but not including HI[WS], with the additional dependent variables remaining unchanged (and listed in Table 3-3), had the lowest AIC (Table 3-3). When models are stratified by group, Urban residents followed the full model, while for the models with only Rural residents and Urban OutWor participants, the inclusion of both HI[WS] and HI[neighborhood] improved the prediction of the individually experienced heat index, as measured by model AIC.

Among all participants, results showed that HI[neighborhood] was significantly associated with HI[individual]. For a 1°C increase in HI[neighborhood], the mean of HI[individual] increases by 0.20°C [95%CI (0.19, 0.21)]. Weather station wind speed (m/s), as an additional environmental factor, was positively associated with HI[individual]. Participants had a 0.50°C [95%CI (0.36, 0.65)] lower mean HI[individual] during weekends and a 1.37°C [95%CI (1.21, 1.53)] higher mean HI[individual] in non-rest time (5 am-midnight) in models accounting for changes in ambient conditions as measured at the nearest neighborhood monitors. This weekend and the non-rest time effect on HI[individual] was largely driven by relationships seen in data from Urban OutWor participants. Rural residents had a 0.43°C [95%CI (-0.56, 1.43)] higher mean HI[individual] compared to Urban residents after adjustment for differences in ambient outdoor temperatures captured by neighborhood monitors. Urban OutWor participants had a 1.22°C [95%CI (-0.05, 2.50)] higher mean HI[individual] compared to urban non-outdoor worker participants.

In models stratified by non-rest time (5 am-midnight) and rest-time (midnight -5 am), only HI[neighborhood] was included in the model selection based on AIC (Table 3-4, Table 3-5). The increased HI experienced in the rural location was more pronounced at rest time (0.10°C [95%CI (-0.85, 1.04)] during non-rest time vs. 1.22°C [95%CI (-0.25, 2.69)] during rest-time). Urban OutWor participants on average had a 1.71°C [95%CI (0.49, 2.92)] higher mean

HI[individual] than Urban residents during non-rest time but a 0.18°C [95%CI (-1.71, 2.07)] lower mean HI[individual] at rest-time (Table 3-4, Table 3-5).

Regression analyses with temperature, instead of HI, from thermometers clipped on shoes, neighborhood monitors and weather station in mixed models were performed and presented in Appendix Table 2, Appendix Table 3, Appendix Table 4. The inclusion of both neighborhood temperature and weather station temperature improved the characterization of the hourly mean participant thermometer temperature based on model AIC. Overall, factors associated with individually experienced temperature were consistent with HI results presented in Table 3-3, Table 3-4, Table 3-5.

We observed differences in relative humidity measurements from weather station and neighborhood monitors (see Appendix Figure 25). The effect of using relative humidity from neighborhood to calculate HI[individual] was minimal compared to using relative humidity from weather station (see Appendix Figure 26). Sensitivity results of individually experienced HI in the *Bias-corrected* dataset are presented in Appendix Table 5, Appendix Table 6, Appendix Table 7, Appendix Table 8, and Appendix Figure 26. On average, HI[individual] was 0.44 °C [95%CI (-0.1°, 2.91)] lower after the correction, and there is no significant difference in the mean risk category frequency (%) of participants in the three population groups (see Appendix Table 5, Appendix Figure 26). Mixed model regression results using corrected HI[individual] as the response showed minimal differences to the main results, and the same significant predictors were obtained (see Appendix Table 6, Appendix Table 7, Appendix Table 8). Additional sensitivity analyses performed examined outlier removal and noncompliance removal in characterizing individually experienced HI diurnally (see Appendix Figure 27), daily average (see Appendix Figure 28), risk classification (see Appendix Figure 29), and mixed models to identify significant predictors (see Appendix Table 9). The results were consistent with the results we have obtained from the Inclusive datasets. Results of the model including pedometer readings <1,000 or ≥25,000 (see Appendix Table 10) were similar compared to the main model results presented in Table 3 and did not alter our main findings on the association between HI[individual] and HI[neighborhood] and/or HI[WS].

3.5 Discussion

This study aims to examine whether temperature and humidity measured at nearby weather station are appropriate for predicting heat stress risk and whether neighborhood heat

index improved the prediction of individually experienced heat index in an urban vs. rural setting. We found that neighborhood level temperature and humidity measurement, in addition to nearby weather station measurements, improved the characterization and prediction of the heat index experienced by individuals. In Rural residents and Urban residents, neighborhood heat index measurements explained more variability in individually experienced heat index compared to weather station measurements (Table 3-3). When both HI[neighborhood] and HI[WS] were included to explain the variance in HI[individual] in Rural residents, the effect size of HI[neighborhood] (0.17°C) was greater compared to that of HI[WS] (-0.06°C), indicating a 1°C increase of HI[neighborhood] is associated with a greater change in HI[individual] compared to a 1°C increase of HI[WS]. It is interesting that a 1°C increase of HI[WS] was associated with a 0.06°C [95%CI (0.02, 0.10)] lower HI[individual] when adjusting for HI[neighborhood] and other individual level factors. A possible explanation is that as shown in Figure 3-1, HI[WS] was higher in the mornings compared to late afternoon and evenings while HI[individual] was a little higher in late afternoons and evenings in the rural location. This result may reflect adaptations by participants to avoid the hottest parts of the day by spending more time indoors with air conditioning between 10am and early afternoon and spending time outdoors or in non-air-conditioned indoor space when it was cooler.

We also found that there was a time window (approximate 8 am-8 pm) when HI[individual] was significantly overestimated by both WS and neighborhood monitors; outside this time window, however, HI[individual] was significantly underestimated (Figure 3-1). Dwelling characteristics including thermal mass [34], no or limited air conditioning use, insufficient night ventilation, human presences, and heat emitting objects such as a working burner/television/refrigerator within the indoor environment are likely reflected in the results showing underestimation of HI[individual] by neighborhood and regional monitors at night. Rural residents on average experienced a higher heat index exposure than Urban residents, even after controlling for differences in ambient conditions, particularly during rest time compared to non-rest time (1.22°C vs. 0.10°C). This suggests that relative to urban residents, rural residents may experience heightened risk to dangerous heat index exposure at a given ambient heat index measured at a nearby weather station, particularly during the nighttime.

In urban outdoor worker participants, weather station measurements explained more variance in HI[individual] compared to neighborhood monitors. This could be explained by

outdoor work occurring away from residences and likely closer to downtown areas. Being an outdoor worker was associated with a 1.71°C [95%CI (0.49, 2.92)] higher mean individually experienced heat index in non-rest time, confirming that outdoor workers are likely at an increased risk of reaching dangerous exposure levels compared to non-outdoor workers in an urban setting. Interestingly, outdoor workers in this study had a 0.18°C [95%CI (-1.71, 2.07)] lower mean individually experienced heat index exposure in rest time, suggesting this population may preferentially seek cooler settings during non-work times to recuperate from daytime heat index exposure.

We also found that neighborhood level heat index measurements served as a better predictor of HI[individual] risk classification than weather station data (Figure 3-3). The risk of overexposure to heat index would be underestimated if weather station data alone were used. This result in residents was consistent with the results for outdoor workers presented in the study by Wang *et al.* (2019), which showed that weather station data alone would recommend fewer person-hours into the most protective work-rest schedules compared to individually experienced temperatures [19]. It is not surprising to find neighborhood heat index was a better predictor of HI[individual], considering neighborhood monitors were much closer to participants' homes and other studies have shown that microclimate conditions varies spatially on local neighborhood scales [35]. As continuously sampling individually experienced heat index of everyone who may be at risk in a large population is unrealistic, neighborhood microclimate measurement is a feasible step forward in downscaling heat index exposure measurement data generated at weather stations. Neighborhood heat index measurements could be used by public health professionals to better identify neighborhoods for interventions to minimize exposure during extreme heat events.

Our finding that weather station HI was significantly associated with individually experienced HI was consistent with the findings revealed in the study by Bernhard *et al.* (2015) and Mac *et al.* (2018) [14, 15]. However, body fat (%) and income level, which were identified as significant factors associated with individually experienced temperatures in both urban and rural participants in the study by Bernhard *et al.* (2015), were only identified as significant factors among outdoor workers in this study. Considering the differences in results across these studies, we think it is worthwhile to include these factors in future studies on individually experienced heat index exposure.

Identification of who, when, and where people are truly exposed to extreme heat during heat wave days is critical for the effectiveness of heat warning systems. The effectiveness of heat warning systems depends on accurate weather forecasts of high temperature and humidity, appropriate heat-stress thresholds to trigger alerts, efficient mobilization of local agency actions, and communication and confirmation that affected residents change their behavior in response to alerts [8]. While regional weather station monitoring is a reliable and accessible source of temperature and humidity measurement, we explored more factors influencing exposure experienced by individuals in an urban vs. rural setting while using weather station measurements to account for ambient heat index. These factors included neighborhood-level temperature and humidity, human behaviors, and body measurements. We found a rural setting and outdoor worker occupation are factors associated with higher individually experienced heat index. Among outdoor workers, we found age and body fat (%) are negatively associated with HI[individual] while physical activity was positively associated with HI[individual], most likely through behavior modification effects. Our results support the integration of risk factors including body metrics and physical activity to customize personal WBGT exposure, such as the Heat Shield platform designed for outdoor workers [36]. We also found that weekdays, non-rest time (5 am-midnight) and higher wind speed are associated with higher individually experienced heat index exposure. By incorporating these identified factors above and potentially more factors influencing heat index exposure at the individual level, we can better predict places and times dangerous heat index exposure may be experienced by individuals.

Our findings that neighborhood level heat indexes are better predictors of individually experienced heat indexes suggest additional measurement and more accurate accounting of variations due to microclimates in alert systems could help local agencies and neighborhood leadership better identify vulnerable residents and target neighborhood level mitigation strategies such as greening, which is likely a primary driver of neighborhood-level temperature differences in urban areas [26]. Additionally, neighborhood level measurements could help to further tailor warning messages of extreme heat health consequences and encourage resident engagement and behavior change in response to warnings [9, 37-39]. Findings from the present study suggest tailored messaging should focus on indoor environments as well as outdoor conditions, with elevation or reduction of risk messaging considering household risk factor status (*e.g.*, elderly,

dwelling without air conditioning, poor fitness, overexertion during work or leisure, minimal time spent outdoors).

There were some limitations of this study. A few factors influencing the air temperature measured by the thermometer clipped to participant's shoe could not be quantified. For example, solar radiation, radiation reflected by grounds/floors, type of shoe (sandals vs. leather shoes vs. cloth shoes), were not accounted for in this study. Solar radiation and body heat can increase the temperatures measured by thermometers on the shoe. Still, we placed the thermometer on the shoe to maximize comfort and minimize body heat impact. The position of the iButton facing down on the shoe reduced the solar radiation impact but may not be able to eliminate it. A radiation shield could be designed for use in future studies to reduce radiation impact on thermometer temperatures. The upper outlier removal and bias correction analyses were attempts to remove these artifacts. In sensitivity analyses, the outlier removal and bias correction effects were minimal in linear mixed models and the characterization of risk classifications (see Appendix Table 6, Appendix Table 7, Appendix Table 8, Appendix Table 9, and Appendix Figure 27, Appendix Figure 28, Appendix Figure 29). We did not use the wet bulb globe temperature (WBGT), a more comprehensive environmental heat measurement that incorporates temperature, humidity, wind speed, and solar radiation [40, 41], to estimate the individually experienced heat in this study because solar radiation exposure was difficult to estimate based on the limited data available to estimate indoor versus outdoor locations for each person-hour. We found two participants continuously experienced HI in Danger and Extreme Danger categories at night (Appendix Figure 21, Appendix Figure 22), which may be due to lack of air-conditioning at home, insufficient indoor ventilation, or potential measurement error. The impact of these person-hours on the main results were minimal in risk classification in the sensitivity analysis (Appendix Figure 24). Potential sources of artificial temperature spikes, such as proximity to warm objects (*e.g.*, working electronics), need be examined in future studies examining nighttime heat index exposure. The influence of daily steps on the relationship between HI[individual] and HI[neighborhood] and/or HI[WS] were minimal in the present analysis (Table 3-3 and Appendix Table 10), however we note limitations in the use of pedometers for estimating daily steps [42-45]. Use of accelerometers in future studies would provide a more accurate representation of the influence to steps on individually experienced heat index [46, 47].

3.6 Conclusions

In conclusion, neighborhood heat index measurement improved the prediction of individually experienced heat index in addition to weather station measurement in the rural setting, and neighborhood heat index alone served as a better predictor in the urban setting. After adjusting for ambient environmental conditions, individually experienced heat indexes in the rural setting were on average 0.43°C [95%CI (-0.56, 1.43)] higher than that in the urban setting. weather station and neighborhood heat index measurements significantly underestimated the Extreme Danger category exposure in all groups and significantly underestimated the Caution category exposure in rural participants only. Weekdays, non-rest time (5 am-midnight), and higher wind speed were significantly associated with higher individually experienced heat indexes. This study is a novel approach to estimate individually experienced heat index exposure in an urban vs. rural setting considering regional weather, local microenvironments, and human behaviors. Understanding individually experienced heat index can help improve public health strategies to minimize adverse health outcomes associated with extreme heat. The incorporation of human behavior data beyond daily steps, more biomedical and health condition data, and indoor/outdoor time differentiation into the characterization of individually experienced heat index exposure is an important next step. This could reveal further factors influencing individually experienced heat index which can be used to improve the prediction of individually experienced heat index exposure.

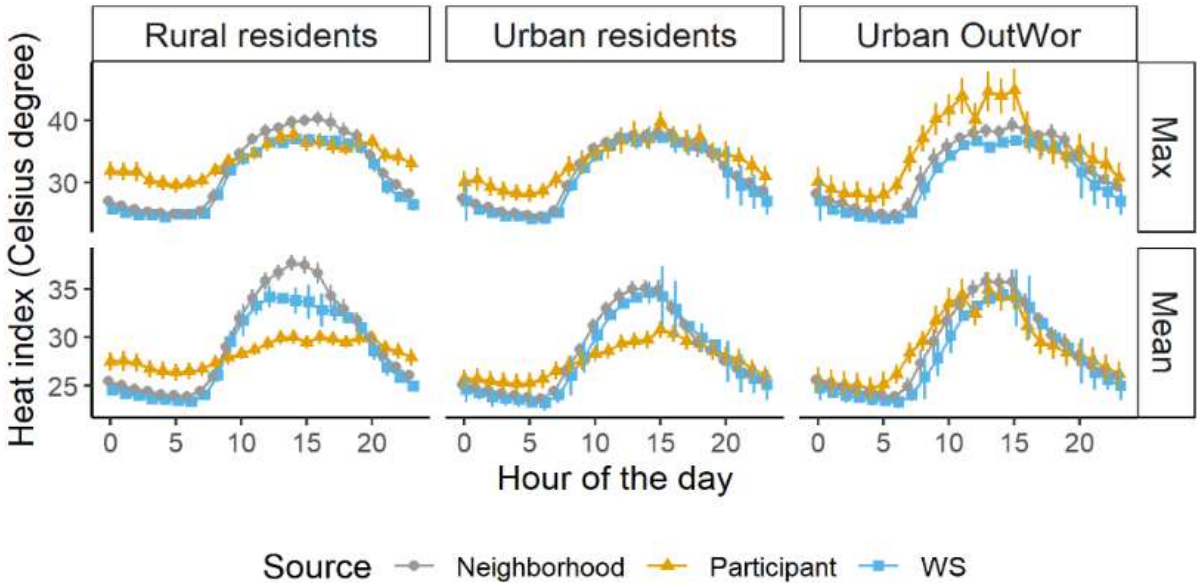

Figure 3-1 Diurnal pattern of maximum and mean HI[individual] (yellow triangle) compared to HI[neighborhood] (gray dot) and HI[WS] (blue square) in Rural residents (participant N=88, neighborhood iButton N=13, weather station N=4), Urban residents (participant N=57, neighborhood iButton N=18, weather station N=2), and Urban OutWor (participant N=32, neighborhood iButton N=11, weather station N=2). The 95% confidence intervals were shown. HI[individual] was calculated from participant iButton temperatures and the closet weather station relative humidity. Each participant wore the monitor for 7 days.

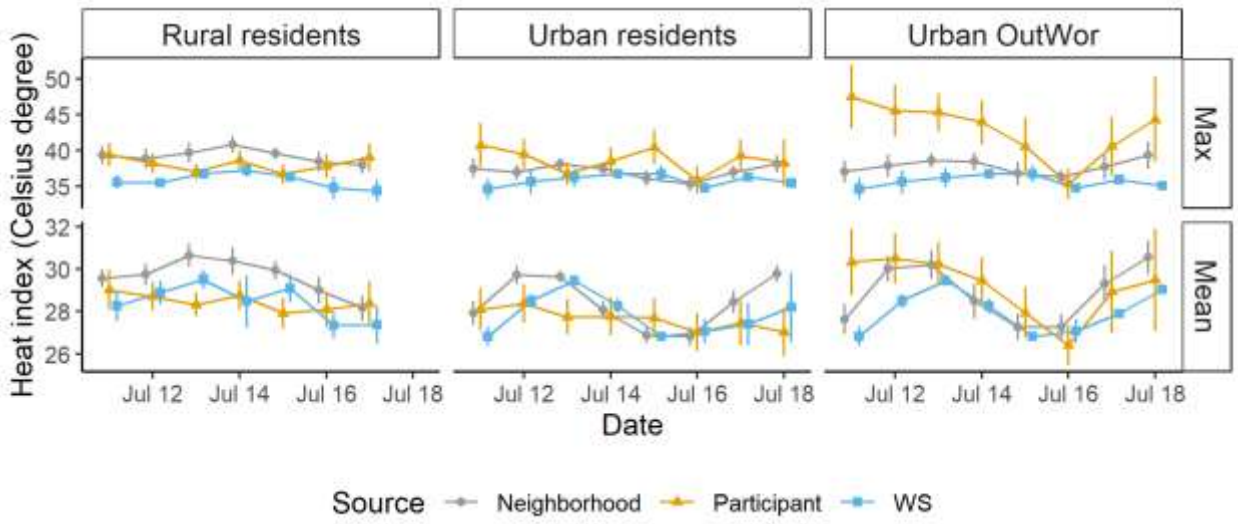

Figure 3-2 Date pattern of maximum and mean HI[individual] (yellow triangle) compared to the matched HI[neighborhood] (gray dot) and HI[WS] (blue square) in Rural residents (participant N=88, neighborhood iButton N=13, weather station N=4), Urban residents (participant N=57, neighborhood iButton N=18, weather station N=2), and Urban OutWor participants (OutWor) (participant N=32, neighborhood iButton N=11, weather station N=2). The 95% confidence intervals were shown. HI[individual] was calculated from participant temperature and weather station relative humidity. Each participant wore the monitor for 7 days. Only person-days with 24 hours of individually experienced HI data are included and 2,492 person-hours were excluded compared to Figure 3-1 dataset. July 15th and July 16th were weekends.

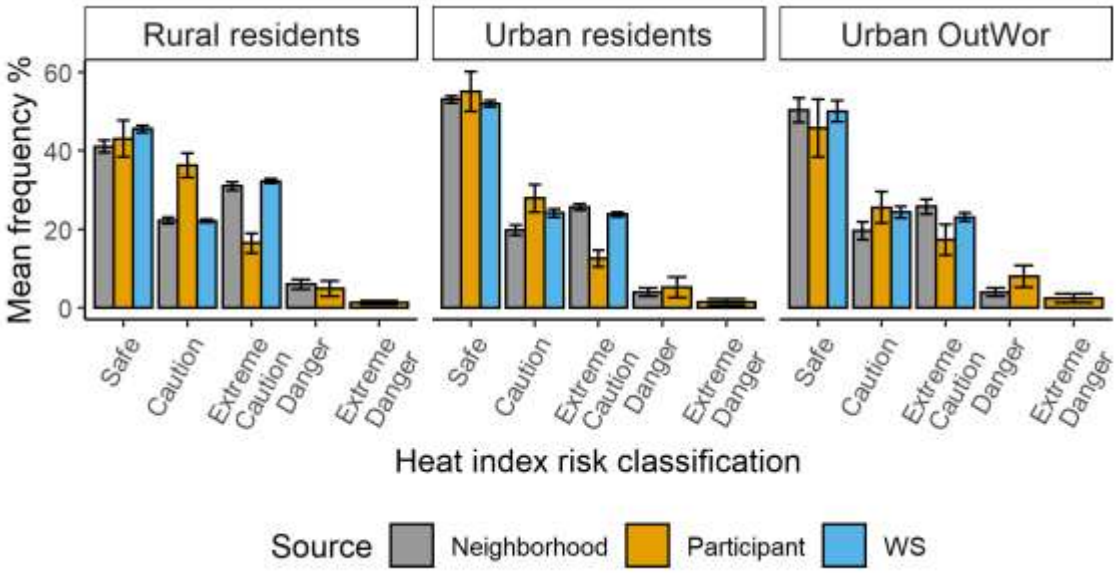

Figure 3-3 Mean frequency % of risk classification based on heat index in Rural residents (N=88), Urban residents (N=57), and Urban OutWor (N=32). Frequency % = Frequency of each risk classification/total person-hours of each participant. The frequency % in each risk classification was averaged in three population groups, respectively. The 95% confidence intervals were shown.

Table 3-1 Participant demographics and characteristics

Settings	Urban setting		Urban setting		Rural setting
Group	Urban OutWor	p-value(1)[a]	Urban residents	p-value(2)[a]	Rural residents
Participant number	32	NA	57	NA	88
Median age (range), years	39.5 (21-60)	0.03*	45 (20-69)	0.17	54 (19-67)
Gender-Female	32 (100%)	NA	57 (100%)	NA	88 (100%)
% Black or African American	30 (94%)	NA	55 (96%)	NA	88 (100%)
Employed	32 (100%)	8.84E-05*	34 (60%)	0.06	37 (42%)
Pedometer daily steps (Mean, range)	5782 (1713-10676)	0.02*	4548 (1080-7872)	1.00	4546 (1257-12740)
Central air conditioning at home					
Yes	12 (38%)	0.62[b]	36 (63%)	0.06[b]	21 (24%)
No	6 (19%)		11 (19%)		17 (19%)
Missing data	14 (44%)		10 (18%)		50 (57%)
Education					
< High School Diploma (or Equivalence)	14 (44%)	0.677[b]	29 (51%)	0.73[b]	40 (45%)
≥ High School Diploma (or Equivalence)	18 (56%)		28 (49%)		46 (52%)
Missing data	0 (0%)		0 (0%)		2 (3%)
Annual household income					
< $20,000	22 (69%)	0.98[b]	37 (65%)	1[b]	57 (65%)
≥ $20,000	10 (31%)		19 (33%)		28 (32%)
Missing data	0 (0%)		1 (2%)		3 (3%)
Body measurement					
BMI (Median, range) from check in session	34.31(19.3-52.3)	0.19	35.8 (24.7-60.3)	0.57	36.6 (19.5-64.8)
Obese (BMI ≥30.0) from check in session	22 (69%)	0.42	45 (79%)	0.97	71 (81%)
Body fat % (Median, range) from check in session	42.4 (22.9-52.8)	0.04 *	45.2 (25.7-54.7)	0.04 *	47.3 (25.3-70.6)

Note: '*' denotes a statistically significant difference with p-values < 0.05. NA not applicable.

[a]p-value(1) was obtained from comparison between Urban residents and Urban OutWor, p-value(2) was obtained from comparison between Urban residents and Rural residents in the same category.

[b]Pearson's Chi-squared test for available data only.

Table 3-2 Distance between participant home and the nearest neighborhood monitor and the nearest weather station

Group	Temperature sources	Distance to participant home (kilometer) mean and 95% confidence interval
Rural residents	Neighborhood monitor	3.64 (2.59, 4.70)
	Weather station	50.12 (4.86, 5.16)
Urban residents	Neighborhood monitor	4.47 (2.89, 6.06)
	Weather station	12.37 (11.28, 13.46)
Urban OutWor	Neighborhood monitor	4.39 (2.52, 6.26)
	Weather station	10.77 (8.81, 12.73)

Table 3-3 Linear mixed model fixed effect predictors of individually experienced HI in 24 hours

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	159992.60	75521.80	51745.30	31346.60
HI[WS] only AIC	160200.10	75619.80	51809.00	31368.70
HI[neighborhood] only AIC	159990.60	75529.00	51743.40	31389.00
Model pick	HI[neighborhood] only	Both	HI[neighborhood] only	Both
Fixed effects	β (95%CI)	β (95%CI)	β (95%CI)	β (95%CI)
Intercept	17.66 (8.83, 26.49)	19.32 (6.25, 32.39)	15.39 (-0.14, 30.93)	12.07 (-5.03, 29.19)
HI[neighborhood] (°C)	0.20 (0.19, 0.21)*	0.17 (0.13, 0.20)*	0.20 (0.18, 0.23)*	0.20 (0.12, 0.28)*
HI[WS] (°C)	NA	-0.06 (-0.10, -0.02)*	NA	0.33 (0.23, 0.42)*
Age	0.01 (-0.02, 0.04)	0.00 (-0.05, 0.04)	0.04 (-0.02, 0.09)	-0.01 (-0.09, 0.08)
Education ≥high school	-0.20 (-1.05, 0.66)	-0.68 (-1.96, 0.59)	-0.10 (-1.66, 1.46)	1.07 (-0.51, 2.65)
Annual household income ≥$20K	-0.60 (-1.53, 0.34)	-0.09 (-1.50, 1.33)	-0.29 (-2.09, 1.50)	-1.53 (-3.35, 0.29)
Weekend	-0.50 (-0.65, -0.36)*	-0.29 (-0.47, -0.10)*	0.08 (-0.17, 0.33)	-1.63 (-2.03, -1.23)*
Body fat (%)	-0.05 (-0.12, 0.02)	0.05 (-0.06, 0.16)	-0.10 (-0.22, 0.03)	-0.15 (-0.25, -0.04)*
Non-rest time (5am-midnight)	1.37 (1.21, 1.53)*	0.65 (0.42, 0.87)*	1.56 (1.29, 1.82)*	2.55 (2.12, 2.98)*
Weather station wind speed (m/s)	0.25 (0.20, 0.30)*	0.31 (0.23, 0.38)*	0.29 (0.21, 0.36)*	0.23 (0.11, 0.36)*
Intervention	-0.26 (-0.40, -0.11)*	-0.30 (-0.50, -0.11)*	-0.11 (-0.35, 0.14)	-0.70 (-1.09, -0.31)*
log(mean daily steps)	0.67 (-0.24, 1.58)	0.46 (-0.84, 1.77)	0.86 (-0.79, 2.51)	0.90 (-0.89, 2.70)
Employed	-0.07 (-1.05, 0.90)	-0.83 (-2.15, 0.49)	0.89 (-0.71, 2.48)	NA
Rural resident[a]	0.43 (-0.56, 1.43)	NA	NA	NA
Outdoor worker[a]	1.22 (-0.05, 2.50)	NA	NA	NA

Note: [a]Compared to Urban resident.

'*' denotes a β estimates with a 95% confidence interval did not contain 0.

NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Table 3-4 Linear mixed model fixed effect predictors of individually experienced HI in non-rest time (5 am-midnight)

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	121158.50	57253.60	39113.50	23785.20
HI[WS] only AIC	121332.30	57340.30	39161.00	23804.00
HI[neighborhood] only AIC	121156.80	57260.40	39111.60	23813.50
Model pick	HI[neighborhood] only	Both	HI[neighborhood] only	Both
Fixed effects	β (95%CI)	β (95%CI)	β (95%CI)	β (95%CI)
Intercept	17.91 (9.51, 26.30)	19.06 (6.98, 31.14)	16.75 (1.88, 31.63)	10.60 (-6.53, 27.78)
HI[neighborhood] (°C)	0.20 (0.19, 0.22)*	0.16 (0.13, 0.20)*	0.20 (0.17, 0.22)*	0.21 (0.12, 0.30)*
HI[WS] (°C)	NA	-0.06 (-0.10, -0.02)*	NA	0.30 (0.20, 0.41)*
Age	0.01 (-0.02, 0.04)	0.00 (-0.04, 0.04)	0.03 (-0.02, 0.09)	-0.01 (-0.10, 0.07)
Education ≥high school	-0.16 (-0.97, 0.66)	-0.47 (-1.65, 0.71)	0.01 (-1.49, 1.50)	0.93 (-0.65, 2.52)
Annual household income ≥$20K	-0.74 (-1.62, 0.15)	-0.16 (-1.46, 1.15)	-0.78 (-2.50, 0.94)	-1.09 (-2.91, 0.75)
Weekend	-0.59 (-0.76, -0.41)*	-0.28 (-0.50, -0.06)*	0.20 (-0.11, 0.51)	-2.32 (-2.82, -1.81)*
Body fat (%)	-0.06 (-0.13, 0.004)	0.04 (-0.06, 0.14)	-0.10 (-0.23, 0.02)	-0.16 (-0.27, -0.05)*
Weather station wind speed (m/s)	0.30 (0.24, 0.35)*	0.31 (0.24, 0.39)*	0.35 (0.26, 0.44)*	0.26 (0.12, 0.41)*
Intervention	-0.42 (-0.59, -0.24)*	-0.42 (-0.65, -0.20)*	-0.25 (-0.55, 0.05)	-0.89 (-1.38, -0.40)*
log(mean daily steps)	0.88 (0.02, 1.74)*	0.62 (-0.59, 1.82)	0.97 (-0.62, 2.55)	1.52 (-0.28, 3.31)
Employed	0.14 (-0.79, 1.06)	-0.81 (-2.03, 0.41)	1.43 (-0.09, 2.96)	NA
Rural resident[a]	0.10 (-0.85, 1.04)	NA	NA	NA
Outdoor worker[a]	1.71 (0.49, 2.92)*	NA	NA	NA

Note: [a]Compared to Urban resident.

'*' denotes a β estimates with a 95% confidence interval did not contain 0.

NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Table 3-5 Linear mixed model fixed effect predictors of individually experienced HI in rest time (midnight-5 am).

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	34925.50	17118.30	11224.00	6456.10
HI[WS] only AIC	34979.10	17162.30	11228.20	6455.70
HI[neighborhood] only AIC	34925.20	17117.50	11222.10	6456.00
Model pick	HI[neighborhood] only	HI[neighborhood] only	HI[neighborhood] only	HI[WS] only
Fixed effects	β (95%CI)	β (95%CI)	β (95%CI)	β (95%CI)
Intercept	16.43 (3.22, 29.64)	10.78 (-9.14, 30.68)	15.38 (-8.12, 38.89)	30.26 (4.69, 55.84)
HI[neighborhood] (°C)	0.36 (0.28, 0.44)*	0.51 (0.37, 0.65)*	0.28 (0.15, 0.41)*	NA
HI[WS] (°C)	NA	NA	NA	0.30 (0.15, 0.46)*
Age	0.01 (-0.04, 0.06)	-0.01 (-0.09, 0.06)	0.05 (-0.03, 0.14)	0.01 (-0.11, 0.14)
Education ≥high school	-0.30 (-1.57, 0.97)	-1.35 (-3.26, 0.57)	-0.38 (-2.72, 1.96)	1.44 (-0.91, 3.78)
Annual household income ≥$20K	-0.23 (-1.61, 1.15)	0.07 (-2.04, 2.19)	1.17 (-1.53, 3.86)	-2.90 (-5.59, -0.21)*
Weekend	-0.20 (-0.38, -0.02)*	-0.41 (-0.68, -0.13)*	-0.23 (-0.52, 0.05)	0.16 (-0.22, 0.54)
Body fat (%)	-0.01 (-0.11, 0.09)	0.09 (-0.07, 0.25)	-0.08 (-0.28, 0.11)	-0.11 (-0.27, 0.05)
Weather station wind speed (m/s)	0.05 (-0.05, 0.15)	0.18 (-0.05, 0.41)	-0.07 (-0.20, 0.06)	-0.06 (-0.24, 0.12)
Intervention	0.17 (-0.01, 0.36)	-0.05 (-0.38, 0.27)	0.46 (0.18, 0.75)*	0.15 (-0.23, 0.54)
log(mean daily steps)	0.12 (-1.23, 1.46)	0.17 (-1.78, 2.13)	0.51 (-1.97, 2.99)	-0.86 (-3.52, 1.80)
Employed	-0.69 (-2.14, 0.75)	-0.83 (-2.81, 1.15)	-0.78 (-3.17, 1.61)	NA
Rural resident[a]	1.22 (-0.25, 2.69)	NA	NA	NA
Outdoor worker[a]	-0.18 (-2.07, 1.71)	NA	NA	NA

Note: [a]Compared to Urban resident.

'*' denotes a β estimates with a 95% confidence interval did not contain 0.

NA not applicable. NA in HI[WS] or HI[neighborhood] indicated that HI[WS] or HI[neighborhood]was not included in model selection based on AIC.

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Chapter 4 Manuscript 3

Title: Effect of an Additional 30 Minutes Spent Outdoors During Summer on Daily Steps and Individually Experienced Heat Index

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4.1 Abstract

Spending time outdoors is associated with increased physical activity; however high ambient temperature/humidity together with built environment features in urban versus rural environments, may influence physical activity. We conducted an intervention trial with 89 urban and 88 rural participants performing normal activities on Days 1-2 (baseline) and spending an additional 30 minutes outdoors on Days 3-7 (intervention) in the summer. Participants wore a pedometer with real-time visual feedback to track daily steps taken and a thermometer clipped to their shoe to track temperatures experienced individually. Hygrometer-thermometers were deployed in participants' neighborhoods to collect finer resolution ambient heat indexes in addition to regional weather station measurements. Using linear mixed effects models and adjusting for ambient conditions and individual-level factors, participants on average walked 637 [95%CI (83, 1192)] more steps and had a 0.59 °C [95%CI (0.30, 0.88)] lower daily mean individually experienced heat index during intervention days compared to baseline days. The intervention benefit of increased physical activity was greater in rural residents who were less active at baseline, compared to urban residents. Our results suggest adding a small amount of additional time outdoors may improve physical activity without increasing participants' heat exposure, even during summer in a humid subtropical climate.

Keywords: time spent outdoors, daily steps, summer temperature, wearable thermometer, physical activity

4.2 Introduction

Weather conditions including high temperatures and precipitation levels have been identified as barriers to participation in physical activity [1, 2]. While physical activity generally peaks in summer [1, 3], a lower level of physical activity in summer was noted in Texas residents when the average temperature of the study month was 29 °C (84°F) [4]. Another study showed a moist tropical climate may be one of the strongest deterrents against physical activity in the US, reducing the percent of adults meeting physical activity recommendations by ~20% [5]. Adults in the Southeastern US had the highest prevalence of physical inactivity (28.0%) based on Behavioral Risk Factor Surveillance System (BRFSS) data [6]. According to the World Health Organization, the prevalence of insufficient physical activity among adults is as high as 40-50% in countries in the subtropical or tropical zones such as Saudi Arabia, India, Brazil, *etc.* [7], where high temperatures may be a barrier to physical activity.

Different types of interventions (*e.g.*, one-to-one counselling, self-directed physical activity, supervised physical activity *etc.*) have been conducted to promote physical activity among children, adolescents, and older adults [8-11]. However, a review by Foster *et al.* (2014) suggested the effect of interventions on self-reported physical activity was mixed with significant heterogeneity in reported effects [12]. New procedures are needed to meet perceived convenience, accessibility, safety, and aesthetic requirements in a given climatic condition, especially in humid tropical conditions [5].

As some studies have suggested initiating and maintaining strenuous exercise programs is difficult [13, 14]. Zimmerman *et al.* (2009) suggested the use of anchors such as social norms, habits and a cultural frame to influence people's preferences for action to promote physical activity [15]. Nudging, which alters people's behavior in a predictable way without forbidding any option, has been identified as an effective approach to promote physical activity [16, 17]. For example, Bellettiere *et al.* (2017) found that stair use increased when placing signs at the bottom of stairs to encourage people to go up [18].

Evidence suggests that time spent outdoors is positively related to reduced sedentary time and moderate and strenuous exercise in adults [19-23]. Harada *et al.* showed that time spent outdoors was significantly and positively associated with physical activity measured as daily steps among 192 older adults, and suggested the health benefits of time spent outdoors were primarily mediated by physical activity [24]. Higher frequency of going outdoors was associated

with less likely decline in the activity of daily living score among older adults [25]. Beyer *et al.* suggests the association between time spent outdoors and increased physical activity could be an opportunity to promote physical activity among youth [19]. However, the nudge approach related to time spent outdoors combined with technology support providing visible feedback (*e.g.*, pedometer) for increased physical activity has largely been unexplored [17]. Encouraging even a small amount of additional time spent outdoors, which is positively associated with increased physical activity and reduced sedentary time from previous studies, could increase physical activity.

We hypothesized an intervention of spending an additional 30 minutes outdoors daily beyond normal activity would provide physical activity benefits with minimal risk to increased heat exposure, particularly when people are free to choose the time of day. Summers in Alabama (AL), US are characterized by subtropical temperature and humidity, where the average high temperature is ~33 °C(91 °F), average low temperature is ~22 °C(71 °F), humidity is ~75% and ~12 days with precipitation per month [26]. Participants could freely choose time of the day and activity to spend an additional 30 minutes outdoors, and participants were instructed on methods to avoid heat stress and safely carry out the intervention. Effectiveness may be different across urban and rural settings; therefore, feasibility and compliance of this 'nudge' intervention were estimated in both an urban and a rural setting in AL.

4.3 Materials and Methods

4.3.1. Participant Recruitment and Individual Level Measurements Collection

We screened and recruited urban residents of Birmingham, AL (N=90) and rural residents of Wilcox County, AL (N=90) in partnership with Friends of West End and West Central Alabama Community Health Improvement League during spring and summer 2017. Eligibility criteria included women aged 19-66 and availability to participate for seven consecutive days between July 10th and 21st, 2017. We recruited women participants to reduce variability for the main outcomes of interest and to improve participant recruitment and follow-up based on our previous community-academic partnership research [27]. Additionally, women in AL are approximately 5% more likely than men to not engage in leisure-time physical activity [28]. Exclusion criteria included having medical conditions or taking medication that could prevent them from spending time outdoors or being out of town. Participants started participation

on different days between July 10th and 12th, 2017. Each participant completed seven consecutive days of participation, with study participation concluding between July 17th and 19th, 2017. Potential participants attended an informational enrollment session, provided written consent, and filled out demographic questionnaires and a Physical Activity Neighborhood Environment Survey (PANES) [29, 30]. We asked participants to perform normal activities on Days 1-2 and spend an additional 30 minutes outdoors beyond their normal activities on Days 3-7. We encouraged participants to choose time, activity, and locations to spend additional time outdoors to avoid dehydration, sunburn, or excessive exertion during the hot hours of the day. Participants kept a daily log of their outdoor time and pedometer readings. Participants received three phone calls to address any challenges in wearing the monitors and filling out the daily logs and they completed an exit survey. Data collection instruments are available at https://www.enactalabama.org/summer-2017. PANES score results are processed based on previously published methods, in which a valid score was assigned to participants who completed at least five out of the seven items [31].

Each participant was instructed to wear an iButton thermometer (DS1922L from Maxim Integrated, California) clipped on the shoe and a pedometer (Yamax Digi-Walker SW-200 from Yamax, Texas) clipped at the waist in all waking hours and leave them by their bedside during sleep. Participants clipped the thermometers facing down to avoid direct sunlight. Thermometers recorded temperature every five minutes. Participants were instructed to record their pedometer reading at night on each day without resetting. We collected the height and weight of participants with a stadiometer and a scale (Model PS660 from Befour Inc., Wisconsin) and body water, body fat, and muscle mass with a portable body composition scale (BC-553 from Tanita Corporation of America, Inc., Illinois) at the beginning and end of participation. At turn-in sessions, we downloaded thermometer data and gave a printout of individual temperature results to participants. We stored all data on password-protected computers. This study was registered with clinicaltrials.gov (NCT 03614780) and approved by Virginia Tech Institutional Review Board (15-761).

4.3.2. Weather Station and Neighborhood Measurements Collection

We deployed 43 iButton thermometer-hygrometers (DS1923 from Maxim Integrated, California) in participants' neighborhoods. We placed each neighborhood thermometer-hygrometer in a radiation shield to avoid direct sun exposure [32]. We deployed the

neighborhood thermometer-hygrometers at various locations (*e.g.*, attached to trees in yards or along sidewalks) and recorded their latitude/longitude with a Global Positioning System (GPS). Neighborhood thermometer-hygrometers measured air temperature and relative humidity hourly. We accessed meteorological data, including air temperature, relative humidity, wind speed, precipitation, and location coordinates during the study from weather stations (WS) in AL from the National Climate Data Center Surface Data, Hourly Global dataset (DS3505) [33].

4.3.3. Data Analysis

We geocoded participants' home addresses using the World Geocoding Service in Arc GIS Pro desktop software (from Esri, California). We matched each participant's residence to the nearest neighborhood thermometer-hygrometer and the nearest weather station. Six weather station in AL were matched to a participant home address (see Appendix Figure 30). We calculated the hourly weather station heat index (i.e., HI[WS]) from weather station temperature and relative humidity, and then calculated a daily mean and max HI[WS]. We calculated the hourly neighborhood heat index (i.e., HI[neighborhood]) from neighborhood averaged temperatures and relative humidity, and then calculated a daily mean and max HI[neighborhood] (see Appendix Figure 31).

A total of 178 participant thermometers (89 in Birmingham and 89 in Wilcox County) had valid temperature measurements at turn-in. We removed upper outliers of hourly averaged temperatures (646 out of 28,016 person-hours removed) which resulted in a dataset containing 27,470 person-hours of hourly averaged individually experienced HI (HI[individual]) (°C) from participant thermometers and matched weather station relative humidity. We used "*weathermetrics"* packages for HI calculation in R [34]. We calculated daily mean and max of HI[individual]. The Intent-to-Treat (ITT) dataset contained HI[individual] of 1,046 person-days. Based on daily logs, we removed 120 person-days of potential self-reported intervention-noncompliance (83 out of 522 person-days in rural participants, 27 out of 338 person-days in urban non-outdoor worker participants, and 10 out of 186 person-days in urban outdoor worker participants) to obtain a Per-Protocol (PP) dataset (see Appendix Figure 32). We also performed analysis using the ITT dataset with no outlier removal.

An activity level was assigned to each participant based on reported weekly leisure activity levels in the Godin Leisure-Time Exercise Questionnaire [35]. We summarized self-reported intervention compliance (yes or no), reported difficulty in compliance, and reasons for

non-compliance from daily logs. We explored factors associated with the probability of intervention compliance in a regression model accounting for ambient conditions and individual-level factors [36]. Unrealistic body composition values from five participants were removed (see Appendix Table 11).

We calculated daily pedometer steps by:

$$Steps_{N+1} = Pedometer\ reading_{N+1} - Pedometer\ reading_{N}$$

where N≥ 0 was day number. We removed person-days with negative steps as a minimally processed dataset. Building from our previous decision tree [37], we removed person-days with negative steps based on daily log notes and extreme daily steps <1000 or ≥25,000 [38]. We used this decision tree to further process steps as our primary pedometer dataset. We examined the differences between primary and minimally processed datasets in sensitivity analysis. Data collection and processing flowcharts are presented in Appendix Figure 33.

We fitted linear mixed effects models to test whether steps changed, and whether participants daily mean or max individually experienced HI changed on intervention days compared to baseline, accounting for ambient conditions and other individual-level factors. Models included a random effect term to account for multiple measurements from each participant. We used "*lmer"* function from "lme4" package in R [39]. Primary analyses were Intent-to-Treat. Models include intervention, daily mean and max HI[WS] (°C), daily mean and max HI[neighborhood] (°C), weather station daily mean wind speed (m/s), rain (yes or no), participant age, education (> high school vs. ≤ high school), annual household income (> $20K vs. ≤$20K), employment (yes or no), measured body fat (%), diabetic (yes or no), self-reported health condition (good, poor, fair), activity level (active vs. inactive), and an interaction term between intervention and groups. We determined whether to include HI[WS] or HI[neighborhood] or both to account for ambient conditions from model Akaike Information Criterion (AIC). We computed AIC for three models (both HI[WS] and HI[neighborhood], HI[neighborhood] only, HI[WS] only) and calculated the $\Delta_i = AIC_i - AIC_{minimal}$. The model best estimated has the $\Delta_i \equiv AIC_{minimal} \equiv 0$ [40, 41]. When $\Delta_i \leq 2$, there is no substantial difference between the two models [40, 41]. If one model including HI[neighborhood] only and another model including HI[WS] only had $\Delta_i \leq 2$ with identical other fixed effects, the model including HI[neighborhood] only was reported because neighborhood thermometers were closer to participants' homes than weather station [42]. We ran models in separate groups to examine the

intervention effect across urban and rural settings, and across occupationally and non-occupationally exposed groups. Measured body mass index (BMI) and measured body fat (%) were highly correlated, we included only measured body fat (%) in final models [27]. We dropped nine participants from the analysis because of missing measured body fat (%), annual household income, education, and self-reported health conditions. We ran sensitivity analysis models with intervention terms (intervention & weekday, intervention & weekend) to see if weekend changed the intervention effect. We performed additional sensitivity analysis described above using ITT dataset with no outlier removal.

4.4 Results

Participants' characteristics are presented in Table 4-1. We exclude one participant due to non-compliance with protocol (CONSORT flowchart in Appendix Figure 15). All participants were women and 173 out of 177 (98%) participants self-identified as Black or African American. Thirty-two participants from Birmingham were outdoor workers (i.e., Urban OutWor). Urban OutWor participants were significantly younger (p-value 0.03), had a lower measured body fat (%) (p-value 0.04) and a higher measured body water (%) (p-value 0.02) compared to Urban non-outdoor worker participants (i.e., Urban residents). Prevalence of diabetes was higher among Rural compared to Urban residents (35 out of 88 [40%] vs. 7 out of 57 [12%]). Rural participants on average had a higher measured body fat (%) (p-value 0.04) and a lower measured body water (%) (p-value 0.02) compared to Urban residents. We observed no significant differences in education, annual household income levels, BMI and obesity prevalence when comparing Rural vs. Urban residents, or Urban OutWor vs. Urban residents. When compared to US census data in these two locations, a higher percent of the participants self-identified as African American (95% vs. 71% in Birmingham, 100% vs. 71% in Wilcox County), had high school and above education (91% vs. 86% in Birmingham, 88% vs. 77% in Wilcox County), and had lower median annual household income (<$20,000 vs. $35,346 in Birmingham, <$20,000 vs. $27,237 in Wilcox County) [43]. A total of 166 out of 177 (94%) participants had valid a PANES score. Participants in the urban location had a significantly higher PANES score compared to participants in the rural location (3.4 out of 7 [95%CI (3.0, 3.7)] among participants in the urban location vs. 1.6 out of 7 [95%CI (1.3, 1.9)] among participants in the rural location).

Participants spent an additional 30 minutes outdoors on 736 (83%) intervention person-days. A total of 104 (59%) participants spent an additional 30 minutes outdoors on every

intervention day while only 4 (2%) participants never carried out the intervention (Figure 4-1). There was a statistically significant difference in the compliance days between Rural residents and Urban residents (Chi-Square=7.99, Degrees of Freedom =3, p-value=0.046), but no significant difference between Urban residents and Urban OutWor (Chi-Square=3.29, Degrees of Freedom = 3, p-value=0.35).

The frequency of self-reported difficulty in intervention compliance is shown in Figure 4-2. Participants reported difficulty in intervention compliance on 316 (36%) person-days, and Urban residents reported more person-days with difficulty in intervention compliance compared to Rural residents (126 out of 285 [44%] person-days vs. 128 out of 440 [29%] person-days). We observed similar frequencies of reported difficulty between Urban residents and Urban OutWor (126 out of 285 [44%] person-days vs. 62 out of 160 [39%] person-days). The self-reported reasons for difficulty in intervention compliance are shown in Figure 4-3. Rain, heat, and time conflicts were the leading reasons for intervention compliance difficulties (Figure 3). We presented the factors associated with the probability of intervention compliance in Appendix Table 12. The effect sizes of most fixed effects are small; participants who were physically inactive had a 15.70% [95%CI (8.94%, 22.46%)] reduced probability of intervention compliance.

The population average of individual mean steps on baseline and intervention days are shown in Figure 4-4, where Rural residents and Urban residents walked more steps during intervention although the difference was statistically insignificant (Figure 4-4). In the mixed models, participants on average walked 637 [95%CI (83, 1192)] more steps on intervention days (Table 4-2). We did not find a significant interaction effect between intervention and groups (see Appendix Table 13). In separate groups, Rural residents had a significant increase of 1063 [95%CI (273, 1851)] mean daily steps during intervention days, after accounting for ambient conditions and other individual-level factors (Table 4-2). Participants in urban locations had a smaller increase of steps on intervention days compared to Rural residents (Table 4-2). Participants walked more steps on intervention weekends than intervention weekdays (see Appendix Table 14, Appendix Figure 34). Intent-to-Treat results and Per-Protocol results are similar; we found slightly lower estimated intervention effect in Per-Protocol, with an average 579 [95%CI (5, 1154)] additional steps on intervention days (see Appendix Table 15). Participants had fewer steps on intervention days in the minimal processed dataset compared to

primary dataset, with the β estimate of intervention -271 [95%CI (-960, 418)] in minimal processed dataset (see Appendix Figure 35, Appendix Table 16).

Rural and Urban participants had similar average daily mean or max individually experienced HI on intervention days, but Urban OutWor had significantly lower daily mean or max individually experienced HI during the intervention, after accounting for weather station HI (Figure 4-5). When we included ambient conditions and individual-level factors in models, we found overall participants had a 0.59 °C [95%CI (0.30, 0.88)] lower *daily mean* and a 1.40 °C [95%CI (0.53, 2.27)] lower *daily max* individually experienced HI on intervention days (Table 4-3, Table 4-4). An interaction term between intervention and group was significant (see Appendix Table 17). In separate groups, Rural residents and Urban OutWor participants on average experienced a 0.49 °C [95%CI (0.09, 0.89)] and a 1.74 °C [95%CI (1.09, 2.38)] lower *daily mean* HI[individual] during intervention days, respectively (Table 4-3). Urban OutWor experienced a 6.60 °C [95%CI (4.11, 9.09)] lower *daily max* HI[individual] during the intervention (Table 4-4).

Overall participants had lower daily mean or max HI[individual] on intervention days during weekend compared to intervention days on weekdays (see Appendix Figure 36, Appendix Table 18, Appendix Table 19). ITT results and PP results were similar, with slightly smaller estimated effect sizes in PP (β estimate of intervention -0.59 [95%CI (-0.88, -0.30)] in ITT vs. -0.49 [95%CI (-0.79, -0.20)] in PP on daily mean of individually experienced HI [see Appendix Table 20], and -1.40 [95%CI (-2.27, -0.53)] in ITT vs. -0.99 [95%CI (-1.90, -0.08)] in PP on daily max of individually experienced HI [see Appendix Table 21]). Outlier removal minimally affected the intervention effect on daily mean HI difference (β estimate of intervention -0.59 [95%CI (-0.88, -0.30)] in ITT vs. -0.51 [95%CI (-0.83, -0.19)] in ITT with no outlier removal) (see Appendix Table 22, Appendix Figure 37). Outlier removal affected the intervention effect on daily max HI difference more (β estimate of intervention -1.40 [95%CI (-2.27, -0.53)] in ITT vs. -0.58 [95%CI (-1.93, 0.76)] in ITT with no outlier removal) (see Appendix Table 22, Appendix Figure 37).

Body measurement change ratios (%) are shown in Table 4-5. Overall, participants had a small decrease in weight, body fat and muscle mass and a small increase in body water. These change ratios were only statistically significant in participants who were obese. A -0.29% [95%CI (-0.45, -0.13)] weight change ratio is equivalent to a 0.52 lb. [95%CI (0.23, 0.81)]

weight loss for a participant weighing 180 lbs. at baseline. There was no significant difference in body measurement change ratios in sensitivity analysis including participants with extreme measurement change ratios (see Appendix Table 23).

4.5 Discussions

This study investigates whether spending an additional 30 minutes outdoors daily in summer is feasible in an urban versus rural environment, and if it changes daily steps and individually experienced HI of participants. Rain, heat, and time conflicts were leading factors hindering participants from spending an additional 30 minutes outdoors in both environments. This result is consistent with findings in previous studies [1, 2], suggesting heat is a barrier for physical activity in summer. Since it is hot and humid with frequent storms in the summer in the southeastern states of the US, heat and rain may be barriers to outdoor time and associated physical activity benefits. We found participants who self-identified as physically inactive had a 15.70% [95%CI (8.94%, 22.46%)] lower probability of intervention compliance. These results indicate participants starting with less physical exercise might perceive higher barriers to spending time outdoors, suggesting efforts to improve time spent outdoors among participants with less physical exercise may require initially reducing the amount of time (*e.g.* start with 15 minutes) or other methods of encouraging behavior change.

Participants increased daily steps by 637 [95%CI (83, 1192)] on intervention days. This relation was driven by increased daily steps in Rural residents, who walked a mean of 1063 [95%CI (273, 1851)] more steps (baseline daily 4346 steps, 24% increase) on intervention days. In contrast, Urban OutWor participants, with much higher baseline steps, only had a small increase in daily steps on intervention days. The results suggested that the benefits of the increased time spent outdoors may be more significant in physically less-active participants. The built environment (*e.g.*, sidewalks, trails, recreational facilities) impacts physical activity [44-47]. Birmingham is the 2nd most walkable city in AL while Wilcox County is considered a car-dependent, less walkable location, based on the walk score metric [48]. Among participants, Birmingham was rated as a more activity-friendly, walkable location with more access to recreational facilities compared to Wilcox County in the PANES results, although some neighborhood environment variables in the PANES may not be relevant for rural neighborhoods [30, 49]. These differences in the built environment, could be at least partially explain differences in neighborhood-level microclimates, and might impact the intervention effects on

promoting physical activity among participants. The generalizability of the results presented to other populations with similar or different demographics should be evaluated in future studies. Spending an additional 30 minutes outdoors daily is minimally limited by socioeconomic status (SES), although we acknowledged that conflicts of time/limited free time associated with lower SES from participants were reported (Figure 4-2). We believe our results may be useful to provide an additional intervention method to promote physical activity among populations with similar SES in both urban and rural settings, especially in subtropical/tropical states in the US. Small but significant changes in body measurement change ratios were detected among participants who were obese after participation, suggesting the intervention benefits may be more significant among people with higher BMI.

While previous studies use weather station data to estimate the effect of ambient conditions on physical activity [3, 50-52], in the current study we have additionally measured microclimates experienced by participants within urban and rural neighborhoods and individual HI experienced by participants as they move through outdoor and indoor environments. This is important as previous studies have shown a wide variation in temperature and humidity experienced within cities, suburban, and rural environments [53-58]. Overall, participants experienced lower daily mean or max HI on intervention days after accounting for ambient conditions, suggesting the additional 30 minutes outdoors did not result in increased heat exposure. Urban and Rural participants experienced a similar small change in daily mean or max HIs on intervention and baseline days, while outdoor workers had significantly reduced HI exposure during intervention days. Outdoor workers may have carried out the intervention in the cool hours of the day, thereby reducing their overall daily heat index exposure. Since participants were free to choose the time of day to spend the additional 30 minutes outdoors, we think most of the participants carried out the intervention either on early mornings or after sunset to avoid the hottest hours. Additionally, because the estimated prevalence of home central air-conditioning was not high for participants, outdoor environment may be cooler than homes when participants carried out the intervention, leading to reduced individually experienced HI. However, there was high missingness for the central air-conditioning response, so it is difficult to draw conclusions.

Two baseline days were weekdays while two out of five intervention days were weekends. To remove the weekend effect, we compared the daily mean or max individually

experienced HI on baseline days vs. intervention on weekdays. However, this step considerably reduced the observation sample size. We observed weekends augmented the negative association between the intervention and daily mean or maximum individually experienced HI in participants. Our results show that non-outdoor worker participants increased daily steps during the weekend but did not increase individually experienced heat indexes.

To address the concern that the thermometer on the shoe might pick up high temperatures due to artifacts (*e.g.*, close to warm surfaces) when the actual environment was not hot, we removed upper outliers. The removal had minimal impact on the intervention effect on daily mean HI[individual]. Pedometer data imputation changed the intervention effect substantially.

In future studies, researchers may use pedometers with built-in daily reading features, or accelerometers to monitor physical activity more accurately. The benefits of additional time spent outdoors would likely include increased physical activity and may be more pronounced after longer term compliance, although this requires further study. Using advanced wearable technologies (*e.g.*, Fitbit, Apple Watch), albeit more expensive, to incorporate heart rate, time spent in different intensity activity, energy expenditure and total distance to measure physical activity more accurately would be an important next step to quantify the physical activity benefits. Participants could be further encouraged to engage in physical activity from these additional real-time feedback measures. Benefits beyond improved physical activity, such as improved mental health, an improved sense of well-being and blood pressure *etc.* suggested by previous studies could also be included [59-61].

4.6 Conclusions

In conclusion, providing a nudge to spend a small amount of additional time outdoors daily with pedometer visual feedbacks may be a feasible intervention to promote physical activity. The current study additionally suggests outdoor ambient conditions at neighborhood level, in additional to regional weather station measurements, are an important factor in determining physical activity in both urban and rural environments in summer months. Finally, our study results indicating a stronger intervention effect in the rural environment suggests further study of differences in built environment characteristics across urban and rural landscapes is warranted.

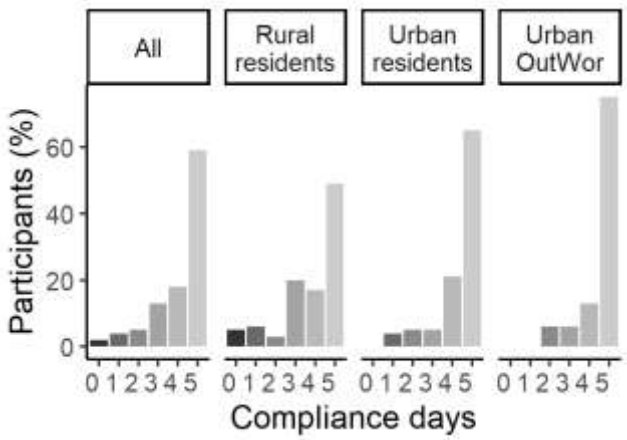

Figure 4-1 Intervention compliance days of participants. Participants (%) = number of participants/total participants ×100% in each compliance days category. Compliance days were days that participant carried out the intervention on Days 3-7 in the study. Pearson's Chi-square tests showed that there was significant difference in the distribution of compliance of person-days between Rural residents and Urban residents (Chi-Square=7.99, Degrees of Freedom =3, p-value=0.046), but no significant difference between Urban residents and Urban OutWor (Chi-Square=3.29, Degrees of Freedom = 3, p-value=0.35).

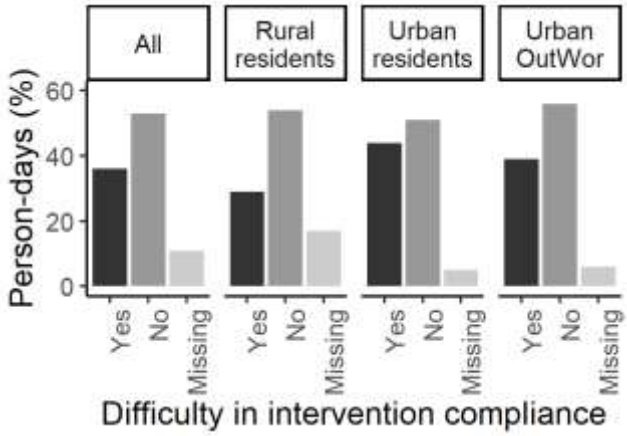

Figure 4-2 Person-days with self-reported compliance difficulty. Missing = participant did not report if she had difficulty in complying the intervention on a person-day. Pearson's Chi-squared test showed that there was significant difference in the binary outcome of reported difficulty between Rural residents and Urban residents (Chi-Square=8.83, Degrees of Freedom = 1, p-value=0.003), and no significant difference between Urban residents and Urban OutWor (Chi-Square=1.12, Degrees of Freedom =1, p-value= 0.29).

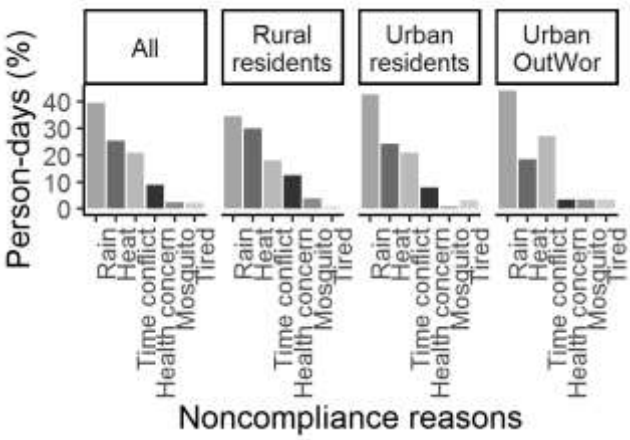

Figure 4-3 Self-reported noncompliance reasons of participants. There was no significant difference in the distribution of noncompliance reasons between Rural residents and Urban residents (Chi-Square=3.04, Degrees of Freedom = 3, p-value = 0.39), or between Urban residents and Urban OutWor participants (Chi-Square=2.93, Degrees of Freedom = 3, p-value = 0.39, p-value = 0.40).

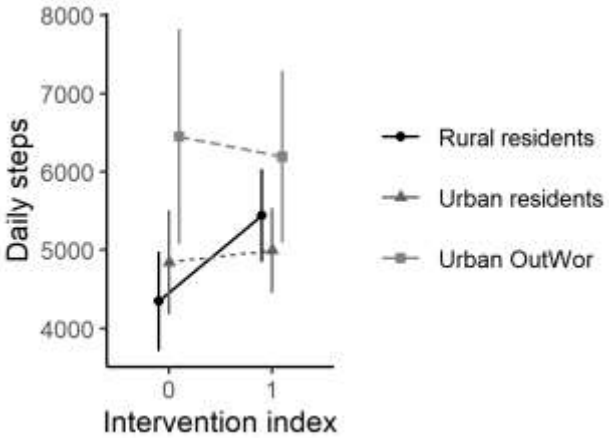

Figure 4-4 The population mean of individual mean daily steps on baseline days (intervention index = 0) and intervention days (intervention index =1) in different population groups. The 95% confidence intervals are shown.

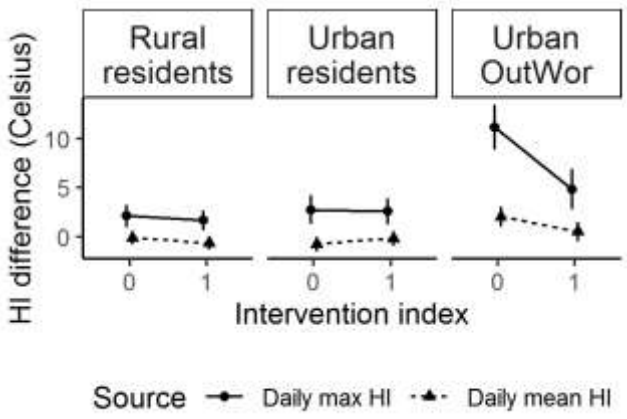

Figure 4-5 The mean HI difference(°C) between individually experienced HI and HI measured at the nearest weather station on baseline days (intervention index = 0) and intervention days (intervention index =1). The 95% confidence intervals are shown.

Table 4-1 Participant demographics and characteristics

Parameters	Urban OutWor	p-value(1)[a]	Urban residents	p-value(2)[a]	Rural residents
Participant number	32	NA	57	NA	88
Median age (range), years	39.5 (21-60)	0.03*	45 (20-69)	0.17	54 (19-67)
Gender-Female	32 (100%)	NA	57 (100%)	NA	88 (100%)
% Black or African American	30 (94%)	NA	55 (96%)	NA	88 (100%)
Employed	32 (100%)	NA	34 (60%)	0.04 *	37 (42%)
Central air conditioning at home		0.42[b]		0.04[b] *	
Yes	12 (38%)		36 (63%)		21 (24%)
No	6 (19%)		11 (19%)		17 (19%)
Missing data	14 (44%)		10 (18%)		50 (57%)
Education		0.52[b]		0.61[b]	
≤High School Diploma (or Equivalence)	14 (44%)		29 (51%)		40 (45%)
>High School Diploma (or Equivalence)	18 (56%)		28 (49%)		46 (52%)
Missing data	0 (0%)		0 (0%)		2 (3%)
Annual household income		0.80[b]		0.90[b]	
<$20,000	22 (69%)		37 (65%)		57 (65%)
≥$20,000	10 (31%)		19 (33%)		28 (32%)
Missing data	0 (0%)		1 (2%)		3 (3%)
BMI (Median, range) from check in session	34.3(19.3-52.3)	0.19	35.8 (24.7-60.3)	0.57	36.6 (19.5-64.8)
Obesity prevalence		0.85[c]		0.52[c]	
Overweight (BMI ≥25 and <30) from check in session	6 (19%)		11 (19%)		13 (15%)
Obese (BMI ≥30.0) from check in session	22 (69%)		45 (79%)		71 (81%)
Body fat % (Median, range) from check in session	42.4 (22.9-52.8)	0.04 *	45.2 (25.7-54.7)	0.04 *	47.3 (25.3-70.6)
Body water % (Median, range) from check in session	41.4 (35.0-52.5)	0.02 *	39.0 (33.3-52.8)	0.02 *	38.0 (19.4-51.8)
Godin activity level		0.20		0.29	
Active	27 (38%)		53 (93%)		77(88%)
Insufficient active	5 (16%)		4 (7%)		11 (13%)

Diabetic		0.98		0.0004*	
Yes	4 (12%)		7 (12%)		35 (40%)
No	28 (88%)		50 (88%)		53 (60%)
Self-reported health condition		0.62[d]		0.29[d]	
Good	25 (78%)		47 (82%)		63 (72%)
Fair	6 (19%)		9 (16%)		19 (22%)
Poor	1 (3%)		1 (2%)		2 (2%)
Missing	0 (0%)		0 (0%)		4 (5%)

Note: p-values were obtained from Welch two sample t-test for continuous variables or Pearson's Chi-square test for categorical variables. '*' denotes a statistically significant difference with p-values < 0.05.

[a]p-value(1) was obtained from comparison between Urban residents and Urban OutWor, p-value(2) was obtained from comparison between Urban residents and Rural residents in the same category.

[b]Chi-squared test for available data only.

[c]Chi-squared test for obese vs. non-obese.

[d]Chi-square test for good vs. less than good.

Table 4-2 Daily pedometer steps on baselines days and intervention days

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	12188 (2304, 22069)	8001 (-6564, 22566)	11120 (-9665, 31906)	23100 (-1962, 48133)
Intervention	637 (83, 1192)*	1063 (273, 1851)*	167 (-828, 1161)	222 (-1163, 1601)
Weather station HI Max(°C)	-244 (-566, 78)	-94 (-701, 513)	-313 (-900, 276)	-377 (-1283, 527)
Neighborhood HI Max(°C)	58 (-115, 231)	193 (-52, 442)	16 (-298, 326)	-71 (-550, 407)
Weather station HI Mean(°C)	44 (-368, 456)	101 (-481, 684)	118 (-669, 908)	-494 (-1882, 894)
Neighborhood HI Mean(°C)	34 (-314, 381)	-260 (-790, 270)	47 (-642, 732)	618 (-431, 1667)
Weather station rain	-479 (-1084, 125)	-686 (-1458, 87)	367 (-921, 1654)	92 (-2070, 2244)

Note: '*' denotes a 95% confidence interval (CI) does not contain 0. Results were Intent-to-Treat. The model for all participants did not include a group factor. Models were adjusted for participant age, education level, annual household income level, employment, measured body fat (%), being diabetic, activity level in Godin questionnaire, and self-reported health condition.

Table 4-3 Intervention effects on daily *mean* heat index (°C) experienced by individuals in different population groups

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	24.45 (19.23, 29.67)	24.47 (15.99, 32.96)	31.58 (22.02, 41.12)	5.43 (-7.78, 18.63)
Intervention	-0.59 (-0.88, -0.30)*	-0.49 (-0.89, -0.09)*	-0.28 (-0.80, 0.24)	-1.74 (-2.38, -1.09)*
HI[WS] Mean(°C)	NA	NA	NA	0.95 (0.59, 1.31)*
HI[Neighborhood] Mean(°C)	0.21 (0.09, 0.34)*	0.01 (-0.19, 0.22)	0.04 (-0.17, 0.25)	NA
Wind speed Mean(m/s)	0.69 (0.23, 1.15)*	0.93 (0.22, 1.64)*	0.56 (-0.16, 1.29)	1.51 (0.39, 2.63)*
Weather station Rain	0.24 (-0.08, 0.55)	0.32 (-0.06, 0.69)	0.03 (-0.62, 0.67)	0.06 (-0.80, 0.92)

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily mean indicates that HI[neighborhood] or HI[WS] daily mean was not included in the model selection based on AIC. Models were adjusted for participant age, annual household income level, education level, measured body fat (%), log(mean daily steps), employment, being diabetic, self-reported health condition, and Godin activity level. Models for all participants did not include a group factor.

Table 4-4 Intervention effects on daily *max* heat index (°C) experienced by individuals in different population groups

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	45.13 (33.44, 56.73)	34.91 (8.80, 51.01)	55.64 (34.37, 76.79)	-10.00 (-59.85, 39.87)
Intervention	-1.40 (-2.27, -0.53)*	-0.24 (-1.36, 0.88)	-0.73 (-2.32, 0.86)	-6.60 (-9.09, -4.11) *
HI[WS] Max(°C)	NA	NA	NA	2.03 (0.71, 3.35) *
HI[Neighborhood] Max(°C)	0.15 (-0.07, 0.37)	0.07 (-0.21, 0.36)	-0.01(-0.43, 0.41)	NA
Wind speed Max(m/s)	0.49 (0.21, 0.76)*	0.23 (-0.13, 0.59)	1.01 (0.53, 1.49) *	0.30 (-0.60, 1.19)
Weather station Rain	-0.05 (-0.98, 0.88)	1.01 (0.02, 2.00)*	-2.30 (-4.22, -0.39) *	-3.52 (-6.74, -0.30) *

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily mean indicates that HI[neighborhood] or HI[WS] daily mean was not included in the model selection based on AIC. Models were adjusted for participant age, annual household income level, education level, measured body fat (%), log(mean daily steps), employment, being diabetic, self-reported health condition, and Godin activity level. Models for all participants did not include a group factor.

Table 4-5 Body measurement change ratios (%) of participants after the intervention

Body measurement change ratio (%)[a]	Mean (95%CI)	Participant N	Obese level[b]	Mean (95%CI)	Participant N
Weight	-0.29 (-0.45, -0.13)*	176	Normal	-0.33 (-1.26, 0.6)	9
			Overweight	-0.3 (-0.75, 0.15)	30
			Obese	-0.28 (-0.46, -0.11)*	137
Body fat	-1.11 (-1.73, -0.49)*	167	Normal	-0.92 (-3.56, 1.71)	9
			Overweight	-1.15 (-2.31, 0.004)	28
			Obese	-1.12 (-1.85, -0.38)*	130
Body water	0.86 (0.34, 1.38)*	167	Normal	0.47 (-1.2, 2.15)	9
			Overweight	0.65 (-0.14, 1.44)	28
			Obese	0.93 (0.3, 1.57)*	130
Muscle mass	-0.87 (-1.42, -0.32)*	167	Normal	-0.42 (-2.39, 1.55)	9
			Overweight	-0.78 (-1.78, 0.22)	28
			Obese	-0.93 (-1.59, -0.27)*	130

Note: '*' denotes a 95% confidence interval does not contain 0.

[a]Body measurement change ratio = (body measurement after intervention – body measurement before intervention) / body measurement before intervention× 100%

[b]Obese level: Normal = (BMI <25), Overweight = (BMI ≥25 and <30), Obese = (BMI ≥30) [62].

4.7 References

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Chapter 5 Manuscript 4

Title: Heat Health Behavior Change during Summer 2020 in African American Alabama Residents

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5.1 Abstract

To investigate how heat-health behaviors changed in Summer 2020 compared to previous summers, our community-academic partnership conducted phone surveys to collect data on cooling behaviors, safety concerns, and preferences for cooling alternatives for 101 participants. Participants indicating they would visit cooling centers declined from 23% in previous summers to 10% in Summer 2020. Cooling centers and use of other public spaces may be less effective in reducing heat-related illness due to safety concerns amid the COVID-19 pandemic and police brutality.

Keywords: COVID-19; police brutality; heat health behaviors

5.2 Introduction

The ongoing coronavirus disease 2019 (COVID-19) pandemic may lead to increased risk of heat-related illness. Heat-related illness risk mitigation strategies before the COVID-19 pandemic – cooling centers, public outdoor recreational areas (e.g., swimming pools, lakes, water parks) – may be less used due to closures and the perception of increased risk of contracting COVID-19 [1]. Additionally, recent exposure/coverage to police brutality among the most vulnerable populations of the US in summer 2020 may change people's perception of safety of visiting public cooling spaces and seeking medical attention if experiencing heat-related symptoms, potentially increasing the risk of heat-related illness [2]. Although staying at home may reduce the risk of contracting COVID-19 and alleviate safety concerns, the lack of at-home air conditioning, high electricity bills or heat-related electrical blackouts may hinder people from staying cool at home in hot weather [1, 3]. Loss of jobs, supply-chain disruption, increased isolation, and restricted healthcare access during the pandemic may also increase risk of heat-related illness [1, 3, 4].

5.3 Intervention

As part of our community-academic partnership-ENACT (www.enactalabama.org), Friends of West End (FoWE) and West Central Alabama Community Health Improvement League (WCACHIL) conducted phone surveys in an urban location (City of Birmingham) and a rural location (Wilcox County) in Alabama, US, respectively, to determine how resident's heat-health behaviors changed in Summer 2020 compared to previous summers, and to relay heat-health mitigation strategies prior to forecasted extreme heat events.

5.4 Place and Time

The phone surveys were conducted in the City of Birmingham and Wilcox County, Alabama in July-September 2020.

5.5 Person

Participants were recruited and enrolled from the established networks of FoWE and WCACHIL. Forty-nine urban participants and 52 rural participants completed the baseline survey, and 48/49 urban participants and 52/52 rural participants completed the follow-up phone survey. The mean age of participants was 52 years, 84% identified as female, and all participants identified as Black or African American (Appendix Table 24). The high proportion of female participants reflects our established networks from prior studies, in which females were more willing to participate [5].

Rural and urban participants were comparable in age, sex, education level, annual household income level, and general health conditions. Participants generally reflect reported U.S. Census demographics in the two sampled locations based on age and education (% ≥65 years and % with high school degree or higher among persons age ≥25 years), and overrepresent persons identifying as Black or African American, female, and lower household income (Appendix Table 25).

5.6 Purpose

The purpose of the phone survey was to mobilize our established community-academic partnership to examine whether and how participants' heat-health behaviors changed due to COVID-19 and recent police brutality in Summer 2020 compared to previous summers and to relay pandemic safe heat-health strategies prior to a forecasted extreme heat event.[6, 7]

5.7 Implementation

We designed the initial and follow-up surveys based on CDC and WHO heat-health guidance.[6, 8] FoWE and WCACHIL completed phone calls using a script (www.enactalabama.org//summer-phone-survey-2020). Participants self-reported use of eight heat-health mitigation strategies in previous summers and then their anticipated use of those same strategies in Summer 2020 in the initial survey. Follow-up surveys were conducted when weather forecasts predicted “Danger” or “Extreme Danger” heat index categories by the National Weather Service over the upcoming week, and participants were asked to report their willingness to use each of the 8 heat-health mitigation strategies during the upcoming forecasted heatwave. Initial phone surveys were completed in June and July 2020 and follow-up phone surveys were completed through September 2020.

5.8 Evaluation

Table 5-1 reports the key results on heat health behavior change, with each participant serving as his/her own control. Fewer participants reported they would use air-conditioned public spaces (e.g., malls, stores, libraries, recreation centers, churches) in Summer 2020 compared to previous summers (23 participants [23%] in previous summers vs. 10 participants [10%] in Summer 2020, p-value 0.02). Results suggest that public air-conditioned cooling centers may not be a major resource to help participants stay cool in the summer, even before the COVID-19 pandemic and high profiles of police brutality cases in 2020. Most participants reported they had used or would use fans, closed curtains or blinds, and check-in with friends and family on hot days in previous summers and in Summer 2020. In urban participants only, a higher percent of participants reported that they would open windows to cool down the house in Summer 2020 compared to previous summers. In Summer 2020, 77% of participants reported they would seek

medical attention if feeling too hot or dehydrated. When examining behavior differences in urban vs. rural participants, a significantly higher percent of urban participants reported they had used or would use, if open, cooler air-conditioned public spaces, public swimming pools or recreational areas compared to rural participants in previous years and 2020. It is important to note most parks, recreation areas, and swimming pools were closed during survey implementation and for example, City of Birmingham swimming pools are still closed as of early April 2021. A higher percent of rural participants reported fan use compared to urban participants in previous summers (43 rural participants [83%] vs. 25 urban participants [51%], p-value 1.0E-03).

A total of 25 rural participants (48%) and 18 urban participants (37%) reported that the recent cases of police brutality had changed their perception of safety for visiting public spaces or recreational areas (Table 5-2). Forty-three participants (43%) felt less safe. One participant explained "*Yes, (I am) afraid that something bad might happen and I might get caught up in it".* Thirty-nine participants (39%) reported the recent cases of police brutality changed their trust in local emergency management or health care providers. Participants explained "*Yes, it (the police brutality) seems like it has gotten worse*" or "*Depend on how ill the person is. It's danger going to ER at night, I would do my best to figure out what to do in case of an emergency at night*". Two participants (2%) reported their or their family/friends' health were affected by other aspects of the recent cases of police brutality. One participant explained "*The lack of trust for the police officer. Too many unsolved death(s) that has occurred from the hand of police officers*". We did not find urban-rural differences in these safety concerns. The changes stratified by age group and how long participants had lived in the community are shown in Appendix Table 26, Appendix Table 27, where a higher % of participants who had lived in the community for

longer-term (6-15 years, and more than 15 years) reported a change in perception of safety compared to participants who had lived in the community for 0-5 years (p-value of 0.002 in Fisher's exact test in Appendix Table 27).

Most participants (95%) in both locations felt they had been able to stay cool so far in Summer 2020 upon completion of the initial survey. However, during the follow-up survey conducted through August and September 2020 before particularly hot weather was forecasted, 21 rural participants (40%) and 17 urban participants (35%) had concerns that they would not be able to stay cool in upcoming hot weather that had been forecasted (Appendix Table 28). Uncertain air-conditioning (AC) capacity (e.g., not enough AC units, AC window unit only), financial concern (e.g., high electricity AC bills, limited income), extreme heat (e.g., participants' quote "*[the weather is] too hot", "the heat was abnormal"*), and housing types (e.g., mobile homes) were the reasons for the concern, reported by 13 (33%), 10 (26%), 4 (10%), and 2 (5%) participants out of the 38 participants, respectively (Appendix Figure 38). These results emphasized the importance of low-cost cooling alternatives at homes.

A total of 70 participants (69%) (36 rural participants and 34 urban participants) reported that they would use a recommended method or methods to keep themselves and friends and families cool during the upcoming heatwave forecasted. Cooling centers (if accessible and open), keeping hydrated, and showers were the top three reported methods (Figure 5-1). Rural participants responded that using cooling centers would be the preferred method while keeping hydrated was the preferred method for urban participants. Twenty-nine (29%) participants reported they would not use any of the recommended methods, and "COVID-19" (14%) and "stay inside (avoiding methods requiring participants to go outside to keep cool)" (8%) were the

top two reasons reported by participants not using recommended methods from both locations (Figure 5-2).

In conclusion, participants were less likely to use public cooling centers or other public spaces in Summer 2020 compared to previous summers due to the COVID-19 pandemic and recent police brutality. Uncertain air conditioning capacity and financial concerns were the top two reasons behind cooling concerns when a heatwave was forecasted.

5.9 Adverse Effects

No adverse events were reported.

5.10 Sustainability

Community-academic partnerships can offer a sustainable method to create and maintain the networks needed to rapidly assess and respond to emergent public health threats.

5.11 Public Health Significance

Systemic racism is a leading public health concern, and police brutality cases, COVID-19, and high temperatures were dangerous concurrent challenges for public health in Summer 2020.[2] Prior to 2020, there was limited access to swimming pools and other public cooling spaces due to redlining and resultant disinvestment in Birmingham and Wilcox County. This study illustrates the feasibility and fast responsiveness of a previously established community-academic partnership in reaching out to residents, collecting information on heat-health behaviors, and sharing heat protective information across an urban and rural location amid the COVID-19 pandemic and recent exposure/coverage to police brutality among the most vulnerable populations of the US in Summer 2020. Our results provide evidence on how heat health behaviors may be changing due to the pandemic and cases of police brutality and this information may be helpful for future heat mitigation intervention development.

Table 5-1 Participants' heat health behaviors in previous summers and Summer 2020.

Location	Participants number (%) in previous summers	Participants number (%) in Summer 2020	P-value[a]
Use cooler air-conditioned public spaces, such as malls, stores, libraries, recreation centers, or churches			
Both	23(23%)	10(10%)	0.02*
Rural	6(12%)	2(4%)	0.27
Urban	17(35%)	8(16%)	0.06
P-value[b]	0.01*	0.047*	NA
Use public swimming pools or outdoor recreational areas (lakes, rivers, water parks)			
Both	17(17%)	13(13%)	0.56
Rural	2(4%)	3(6%)	1
Urban	15(31%)	10(20%)	0.35
P-value[b]	4.0E-04*	0.04*	NA
Worry about not being able to keep cool due to high cost of air-conditioning			
Both	45(45%)	43(43%)	0.89
Rural	22(42%)	21(40%)	1
Urban	23(47%)	22(45%)	1
P-value[b]	0.69	0.69	NA
Open windows to cool down the house			
Both	20(20%)	32(32%)	0.08
Rural	9(17%)	12(23%)	0.63
Urban	11(22%)	20(41%)	0.08
P-value[b]	0.62	0.09	NA
Use fans to keep cool			
Both	68(67%)	73(72%)	0.54
Rural	43(83%)	42(81%)	1
Urban	25(51%)	31(63%)	0.31
P-value[b]	1.0E-03*	0.07	NA
Close blinds or curtains during hottest part of the day			
Both	81(80%)	82(81%)	1
Rural	42(81%)	43(83%)	1
Urban	39(80%)	39(80%)	1
P-value[b]	1	0.80	NA
Check with friends and family during hot days			

Both	89(88%)	91(90%)	0.82
Rural	43(83%)	44(85%)	1
Urban	46(94%)	47(96%)	1
P-value[b]	0.12	0.09	NA

Note: [a]p-values were obtained between response in previous summers vs. the Summer 2020 in the same location in Fisher's exact tests. [b]p-values were obtained between response in the urban location vs. the rural location concurrently in Fisher's exact tests. "*" denotes a statistically significant difference with p-values <0.05.

Table 5-2 Perception of health and safety change due to recent police brutality

Factors	Participants number (%) in Both	Participants number (%) in Rural	Participants number (%) in Urban	P-value[a]
Change perception of safety for visiting public spaces or recreational areas	43(43%)	25(48%)	18(37%)	0.31
Change trust in local emergency management or health care providers	39(39%)	17(33%)	22(45%)	0.23
Affect your health, or health of your family and friends	2(2%)	1(2%)	1(2%)	1

Note: [a]p-values were obtained between response in previous summers vs. in Summer 2020 in the same location in Fisher's exact tests.

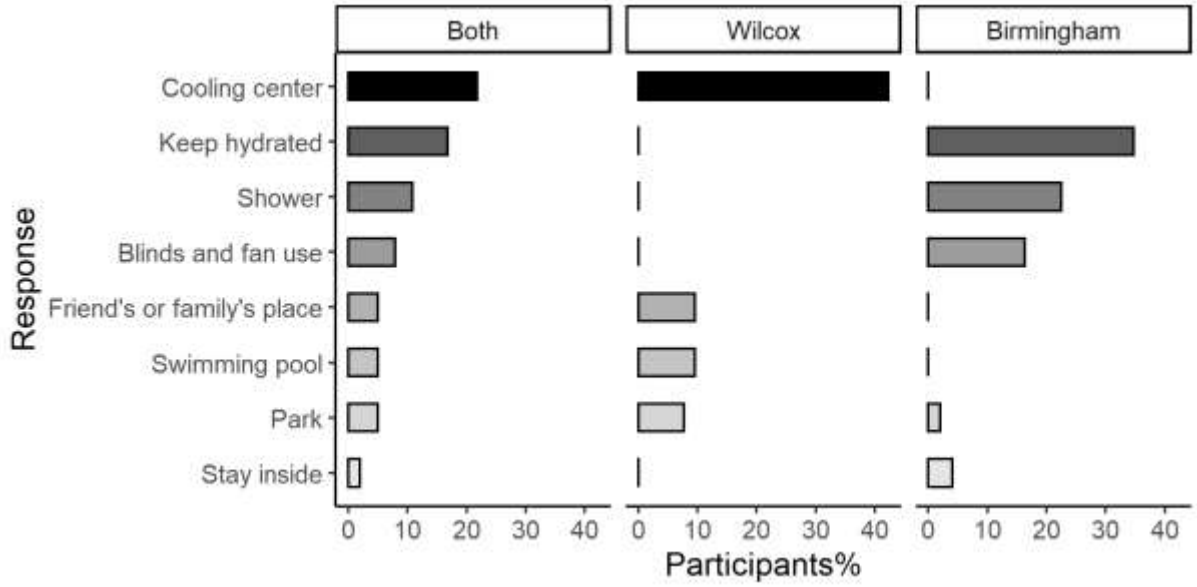

Figure 5-1 Methods that participants reported they would use to keep cool in the upcoming heatwave forecasted in 2020. A total of 36 participants (69%) in Wilcox County and 34 participants (69%) in City of Birmingham reported they would use a method, reporting a total of 36 responses in Wilcox County and 39 responses in City of Birmingham.

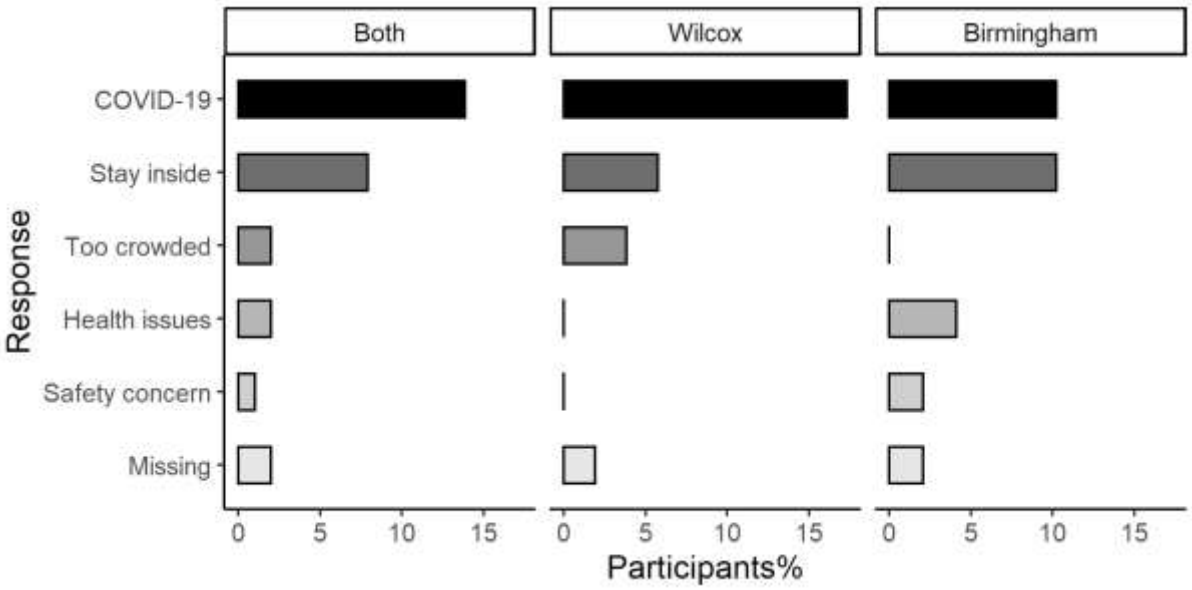

Figure 5-2 Reasons why participants reported they would not use any recommended method to keep cool in the upcoming heatwave forecasted in 2020. A total of 15 rural participants (29%) and 14 urban participants (29%) reported they would not use any recommended method. One participant in Wilcox County and one participant in City of Birmingham did not explain why they would not use any suggested method.

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Chapter 6 Conclusions

It is expected that there will be stronger, more frequent, and longer heat waves in the future. Since heat-related morbidity and mortality in hot weather is still a heavy burden to public health, more accurate estimation of the burden of extreme heat and the identification of vulnerable populations is crucial for intervention and policy development to reduce heat-related health effects.

This dissertation explores the opportunities of more accurate heat index exposure characterization using wearable sensors by participants in the subtropical climate of the Deep South region of the US. This work is a novel approach to estimate heat index exposure as experienced by individuals as they go about their daily activities in an urban and rural setting, with the consideration of the influence of regional and local neighborhood heat index, participants' behaviors, and body measurements. The individually experienced heat index exposure is utilized to monitor participants' heat exposure in a health intervention of spending additional time outdoors to promote physical activity and general health outcomes. The heat safety of outdoor workers, who were a part of the study population, were separately analyzed due to their unique non-climate-controlled working environment and the availability of the well-recognized National Institute for Occupational Safety and Health (NIOSH) heat safety guidelines targeted to workers. With the emerging concurrent challenge of the COVID-19 pandemic and extreme heat in summer, new data on the everchanging heat-health behaviors were collected in this work to inform policy makers and researchers. The collection of studies ultimately serves to bring new knowledge and deepen the understanding of heat index exposure at the individual level in vulnerable populations, which can be useful for policy makers to revise current policies or develop new policies, and for researchers to design novel interventions.

In Manuscript 1, individually experienced Wet Bulb Globe Temperature (WBGT) was estimated, and work-rest schedules were recommended based on either wearable thermometer temperatures or regional weather station temperatures among outdoor workers in the City of Birmingham, Alabama. The outcomes highlighted that outdoor workers were at risk of overexposure to heat due to their non-climate-controlled working environment and relying solely on regional weather station measurements might not provide sufficient rest periods for outdoor workers. This manuscript, together with other published work,[1-7] confirmed the opportunities

of more accurate characterization and classification of heat experienced by individuals among outdoor workers by using wearable thermometers in an occupational setting. The potential heat-health recommendations based on the results include more work-rest periods, arranging strenuous tasks in early morning, and scheduling sedentary tasks (*e.g.*, meetings, trainings, paperwork) during hot hours, *etc.* Important next steps are to collect outdoor workers' continuous physiological responses to heat and synchronize them to the estimated individually experienced WBGTs to further characterize the relationship between exposure and response.

In Manuscript 2, we used a novel approach to estimate heat index exposure as experienced by individuals as they went about their daily activities in an urban and rural setting. Each participant clipped a small thermometer to their shoe during the study. We considered the influence of regional and local neighborhood heat index, human behaviors, self-reported health conditions, and demographics. We showed that microenvironments in neighborhoods were predictive of individually experienced heat index exposures. Rural residents had higher individually experienced heat indexes than urban residents when ambient temperature and humidity were the same, suggesting built environment differences and behaviors of those in the rural location increase heat index experienced by individuals. While it is not practical to place a small thermometer on everyone who may be at a risk of overexposure to heat and the limitations of regional weather stations are well documented, providing a neighborhood level heat index estimation was an attempt to provide more accurate measurements at a finer scale. Our results demonstrated that neighborhood level measurements are feasible, useful, and cost-effective. Our results also provide more evidence that vulnerability to heat among rural populations is underestimated and can be useful in study location selection for future studies. The results may also be useful in developing different heat-health effect remediation policy for urban and rural areas, respectively. This suggestion agrees with recommendations made by other researchers to increase health care access, raise awareness of heat-related health effects through timely alerts/reminders for rest, water, and shade breaks, and provide financial assistance for paying electricity bills for running air-conditioners in rural areas [8, 9]. Providing hydration reminders is emphasized in rural areas because of the high number of agricultural workers in rural settings [8, 9]. While in urban areas, providing more green roofs, more trees and vegetation, more cooling centers, and sustainable urban infrastructure to reduce the heat island effects have been recommended [10, 11].

Manuscript 3 reports the health intervention effect of spending additional time outdoors on physical activity, body measurements (weight, body fat %, body water %), and individually experienced heat exposure. The study explored an important application of the individually experienced heat exposure work: monitoring the heat exposure of participants during the intervention in summertime. The results showed that participants on average walked more daily steps and had lower individually experienced heat index exposure during the intervention periods compared to baseline periods. The results demonstrated the feasibility and effectiveness of the intervention in promoting physical activity while not placing participants at a higher risk of extreme heat exposure. This important benefit-risk characterization can aid in future intervention development via time spent outdoors.

Manuscript 4 examined whether people had different heat-health behaviors during the summer of 2020 due to COVID-19 compared to previous summers. Established heat-related illness mitigation methods, including visiting air-conditioned public cooling centers, water parks, and swimming pools, may be less used to avoid crowd gathering or comply with stay-at-home orders. The results highlighted that fact that less participants reported they would use public cooling centers due to the COVID-19 pandemic, while their at-home cooling methods stayed consistent. Heat-health problems are dynamic and ever-changing with climate change and other public health concerns. This work offers important data on heat-health behaviors in the COVID-19 pandemic.

Overall, the collection of the four studies provides information on the opportunities of more accurate characterization of individually experienced heat exposure in an urban and a rural location in a southern state in the US. We used a wearable-sensor based approach to collect the continuous microclimate data in a relatively large sample size, when compared to previous studies. In addition to regional weather station measurements, we deployed sensors and collected neighborhood-level microclimate measurements to account for the ambient heat near participants' residences at a finer scale. We also applied the individually experienced heat index exposure methods in a behavioral clinical trial to investigate the intervention effect of spending additional time outdoors on physical activity. Individual level factors including demographics, behaviors, and self-reported general health conditions are included to identify the vulnerability characteristics to heat among the participants.

This dissertation adds knowledge to develop potential policies/guidelines for heat mitigation strategy deployment based on the heat burden on targeted populations. The results in this dissertation complement other studies assessing individually experienced temperature/heat index exposure using wearable sensors [1, 3, 4, 6-9] by including the urban-rural comparison, neighborhood level heat measurements, and personal behaviors (*e.g.*, pedometer steps). We show that microenvironments in neighborhoods are predictive of individually experienced heat index exposures, and this effort aligns with other researchers' goals to estimate the risk of heat stress at a finer scale using tools that go beyond regional weather stations [9-15]. We had a more valid and precise estimation of the heat burden among participants, reducing the potential misclassification of participants' heat exposure. In terms of policy indications, this dissertation is in line with WHO's actions for climate change: (1) advocate and raise awareness; (2) strengthen partnerships (*e.g.*, aligning with a community-engaged approach); and (3) enhance scientific evidence [16]. This dissertation is also answering calls from CDC to use heat exposure and their associated health outcome data to have a better understanding of the possible health effects and risks faced by specific groups of people, evaluate heat-health relationships at a local level to plan interventions, and communicate interventions to at-risk populations [17]. Additionally, as found by Kuras *et al.* (2017), participants had a better understanding of their own exposure patterns [13], raising the awareness of heat-related effects and potentially increasing the compliance of heat-related illness prevention recommendations among our participants.

Future work should focus on collection of continuous physiological responses to connect with simultaneous heat exposure measurements to better characterize the exposure-response relationship across different populations. For example, more advanced wearable technology, such as Fitbit and Apple Watch, can be used to collect heart rate, activity intensity and duration. More advanced geographic location trackers can also be used to better estimate the indoor vs. outdoor conditions as participants go about their activities. Another outdoor time intervention with longer duration (weeks to months) can be proposed to study the physical activity benefits and individual level heat safety in summertime and to reveal longer-term intervention utilization and adherence to make the intervention sustainable and effective.

6.1 Reference

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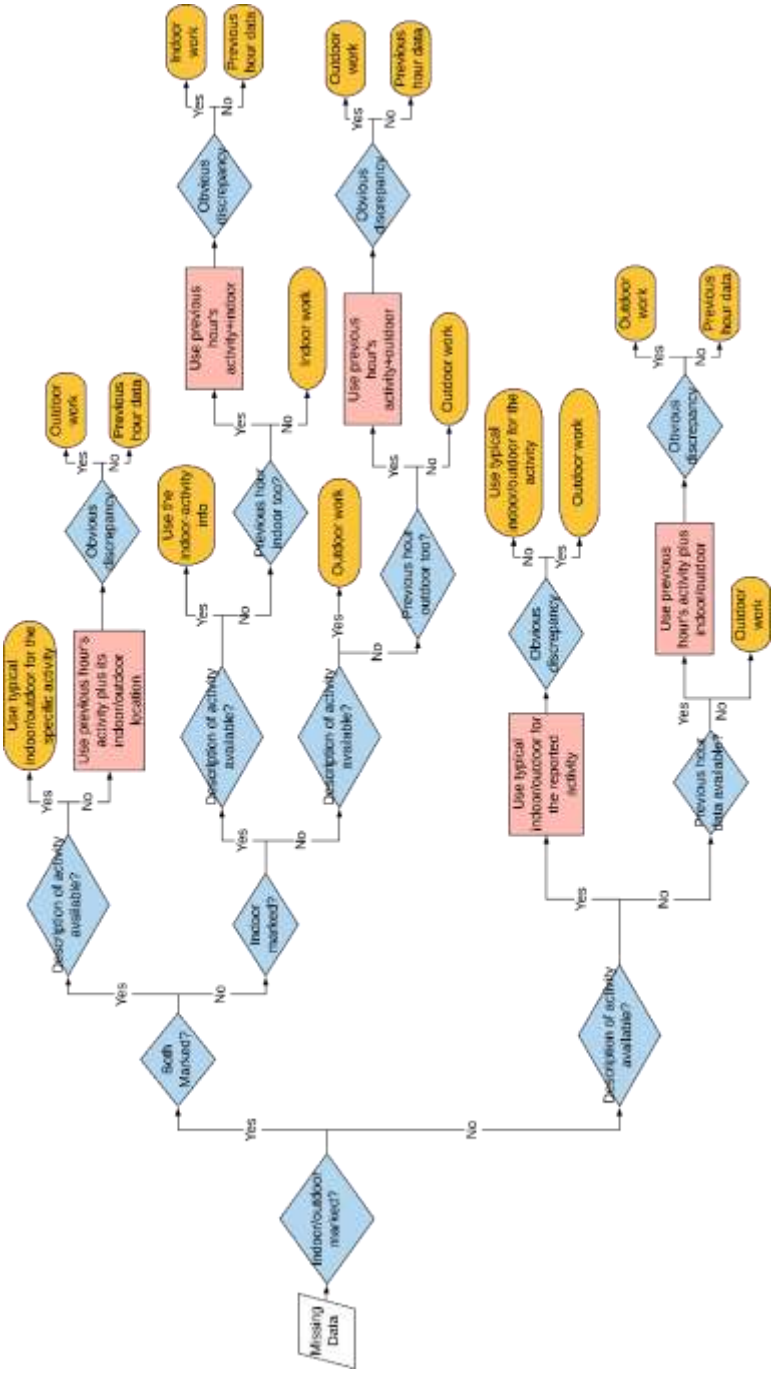
Chapter 7 Appendices

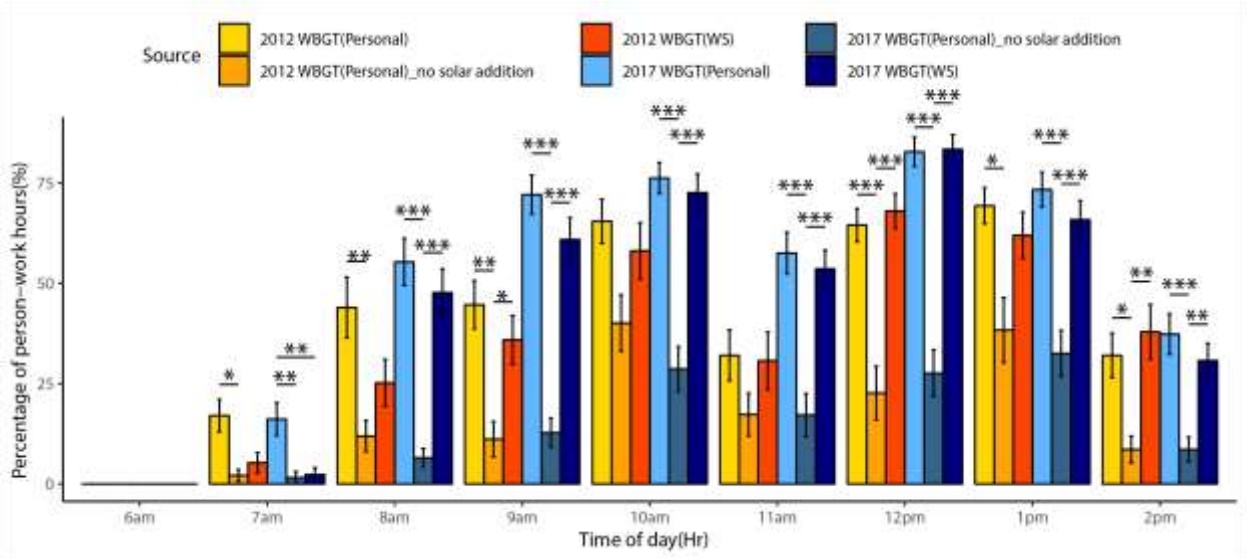
Appendix A Supplemental Materials to Manuscript 1



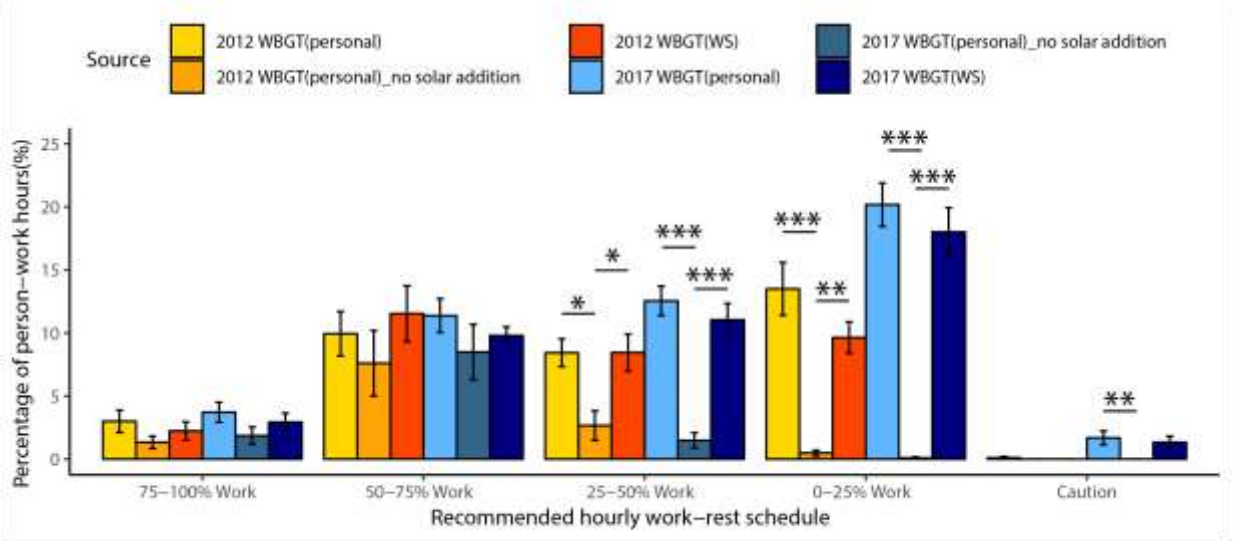
Appendix Figure 1 Decision tree for replacing missing data in the hourly activity log in 2012

Appendix Table 1 Study participant's estimated metabolic rates and corresponding codes for activity based on the logs filled out by each groundskeeper in 2012.

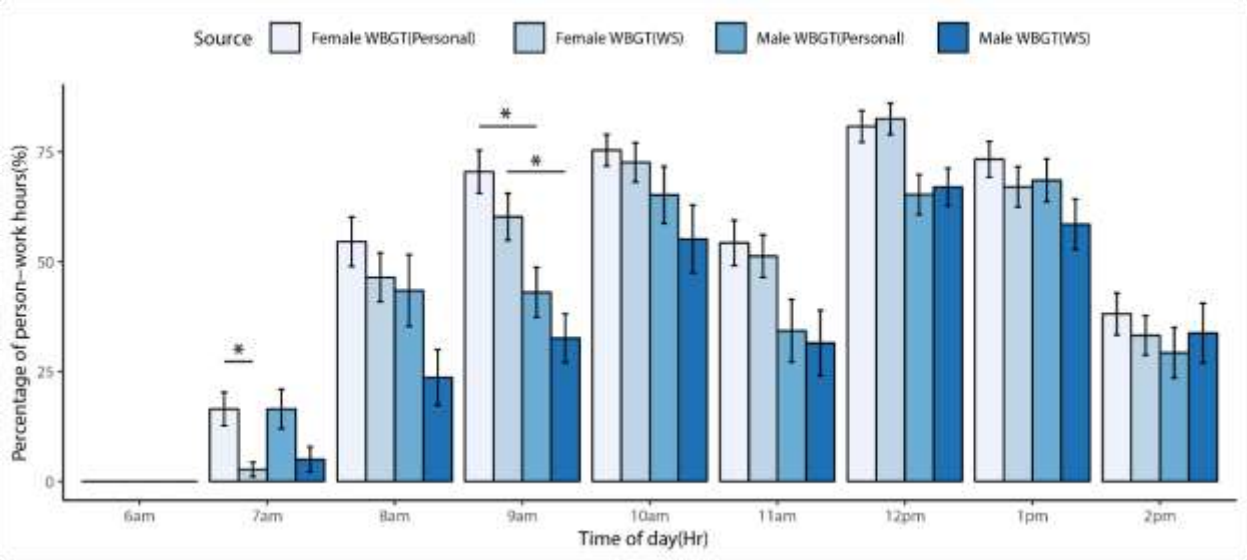
Work Demand Level	Metabolic rate recommended by ACGIH(ACGIH, 2017)	Weight adjusted metabolic rate categorization for work/rest recommendation	Category list from activity description in the hourly log
Rest/Sedentary	115	<147.5	Break Lunch Meeting Rest Watch TV Drive automatic vehicles
Light	180	147.5-240	Off/Leave work Prepare/Start to work
Moderate	300	240-357.5	Bicycle 5-9 mph Drive heavy vehicles Gardening and yard work, weeding General home construction work General at home exercise General work Hand wash or wax a car/truck Home repair Homebuilding tasks Moderate lifting Put groceries away < 50lb Walk at a fast pace
Heavy	415	357.5-467.5	Gym exercise Handle heavy materials
Very heavy	520	>467.5	Pick and shovel work



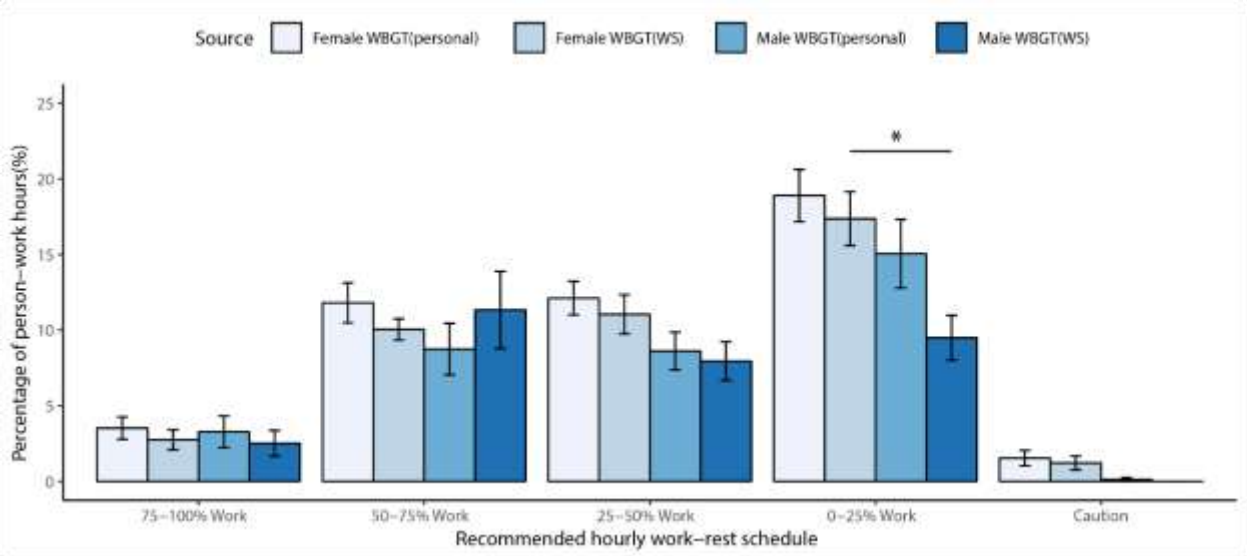
*Appendix Figure 2 Average percentage of person-work hours of WBGT index that exceeds weight adjusted TLV® across all participants in 2012 and 2017 separately(Mean ± Standard Error). Statistical significance symbols: '***' denotes P-value of 0 - 0.001, '**' denotes P-value of 0.001 - 0.01, '*' denotes P-value of 0.01 - 0.05, ' ' denotes P-value >0.05 and no significant difference.*



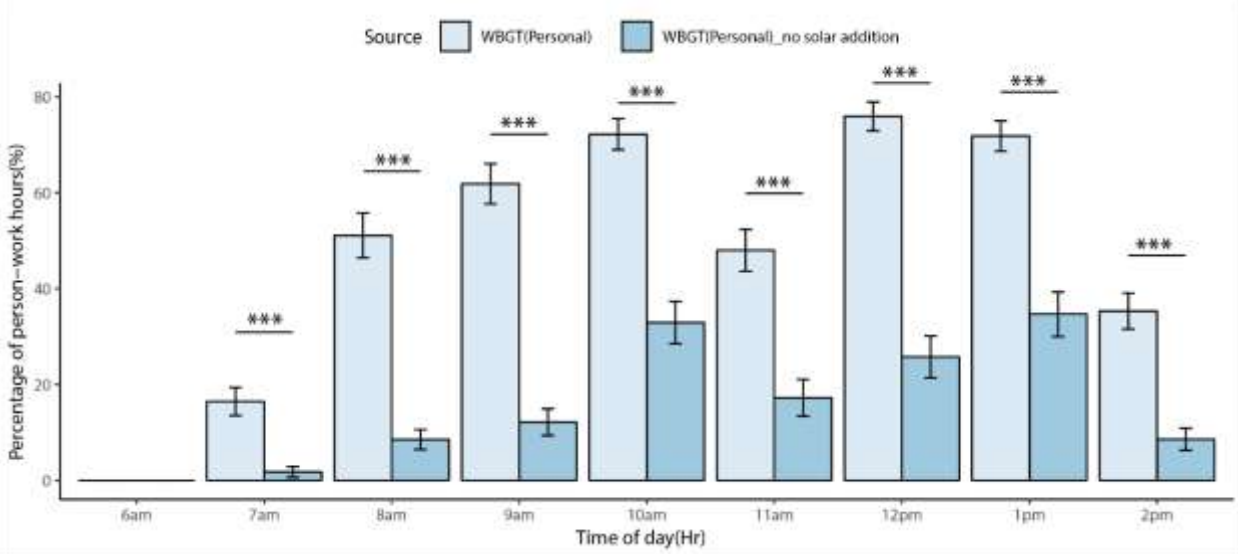
*Appendix Figure 3 Average percentage of person-work hours in recommended work-rest schedule based on WBGT index across all participants in 2012 and 2017 separately (Mean ± Standard Error). Statistical significance symbols: '***' denotes P-value of 0 - 0.001, '**' denotes P-value of 0.001 - 0.01, '*' denotes P-value of 0.01 - 0.05, ' ' denotes P-value >0.05 and no significant difference.*



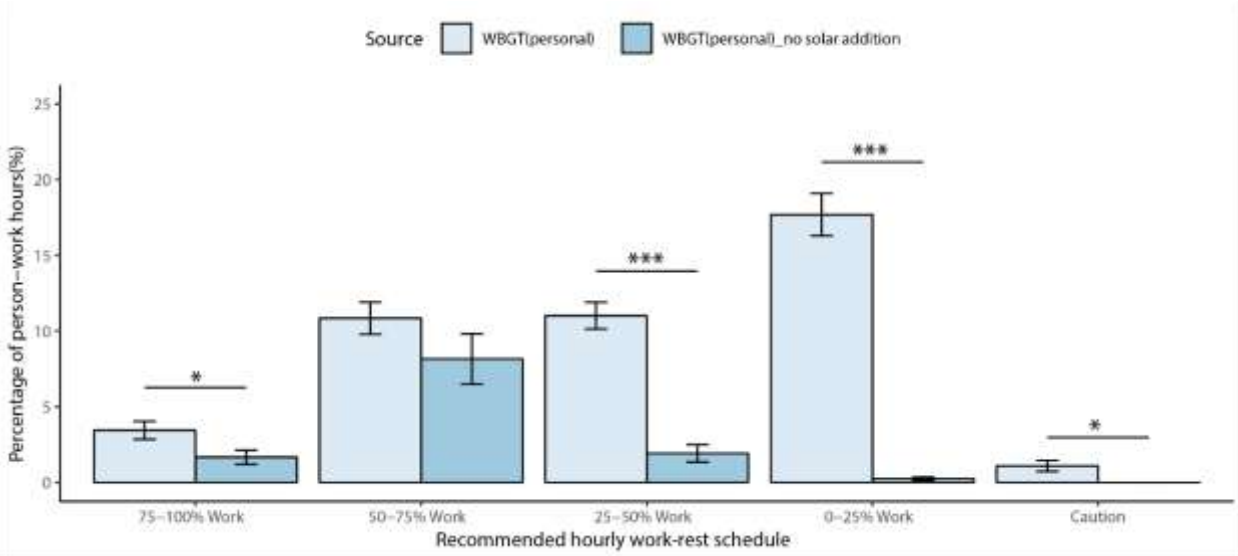
Appendix Figure 4 Average percentage of person-work hours of WBGT index that exceeds weight adjusted TLV® across in male or female participants(Mean ± Standard Error). Student's t-tests were performed between same gender WBGT(personal) and WBGT(WS), and WBGT(personal) or WBGT(WS) in two genders, respectively. Statistical significance symbols: '' denotes P-value of 0.01 - 0.05, ' ' denotes P-value >0.05 and no significant difference.at different hours.*



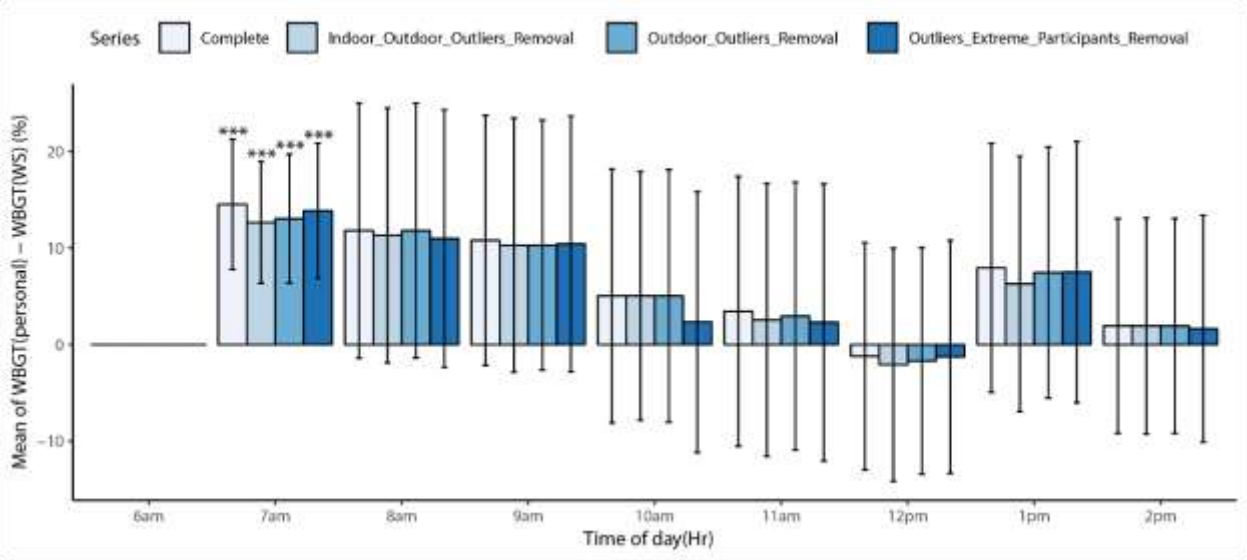
Appendix Figure 5 Average percentage of person-work hours in recommended work-rest schedule based on WBGT index in male or female participants(Mean ± Standard Error). 75-100% Work is 45-60 min work/0-15 min rest per hour, 50-75% Work is 30-45 min work/15-30 min rest per hour, 25-50% Work is 15-30 min work/30-45 min rest per hour, 0-25% Work is 0-15 min work/45-60 min rest per hour. Caution category represents WBGT index that exceeds weight adjusted TLV® when participants were at rest (estimated hourly metabolic rate around 115 Watts) in that person-work hour. Unshown percentage of hours fell into continuous work category. The percentage of person-work hours in Continuous work is 51.9%±2.8% for WBGT(personal) and 57.4%±2.8% for WBGT(WS) in females, and 64.2%±3.6% for WBGT(personal) and 68.7%±4.1% for WBGT(WS) in males. Student's t-tests were performed between same gender WBGT(personal) and WBGT(WS), and WBGT(personal) or WBGT(WS) in two genders, respectively. Statistical significance symbols: '' denotes P-value of 0.01 - 0.05, ' ' denotes P-value >0.05 and no significant difference.at different hours.*



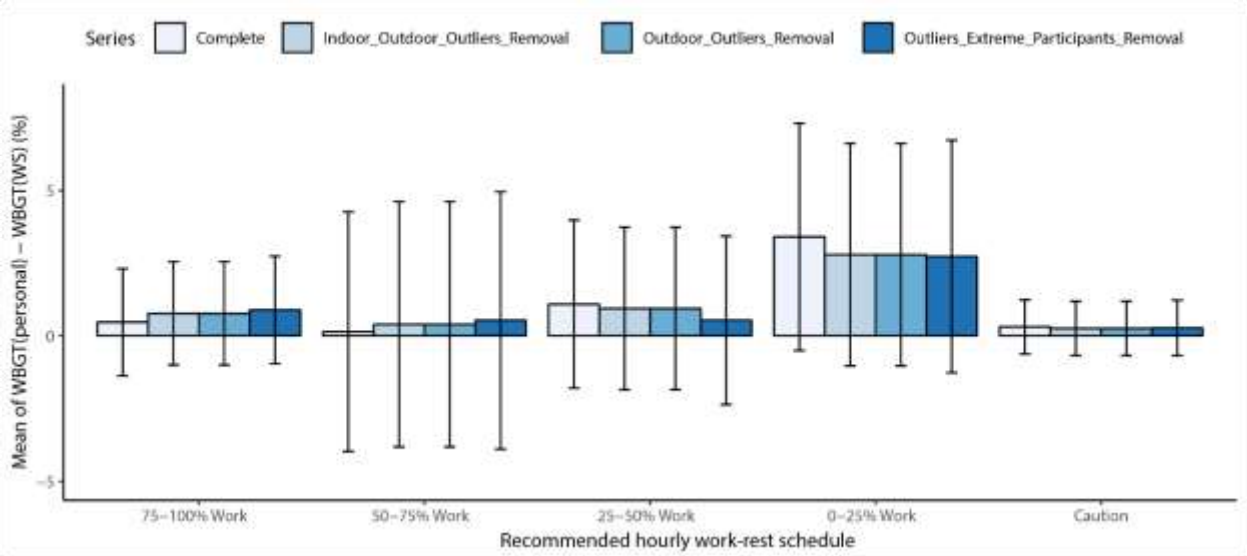
*Appendix Figure 6 Average percentage of person-work hours of WBGT index that exceeds weight adjusted TLV® across all participants(Mean ± Standard Error). WBGT(personal) assumes personal thermometers temperature measurements integrate no solar radiation so that solar radiation is added in WBGT calculation. WBGT(personal-no solar addition) assumes personal thermometers temperature measurements integrate all solar radiation, no solar radiation is added. Statistical significance symbols: '***' denotes P-value of 0 - 0.001, ' ' denotes P-value >0.05 and no significant difference.at different hours.*



*Appendix Figure 7 Average percentage of person-work hours in recommended work-rest schedule based on WBGT index across all participants(Mean ± Standard Error). 75-100% Work is 45-60 min work/0-15 min rest per hour, 50-75% Work is 30-45 min work/15-30 min rest per hour, 25-50% Work is 15-30 min work/30-45 min rest per hour, 0-25% Work is 0-15 min work/45-60 min rest per hour. Caution category represents WBGT index that exceeds weight adjusted TLV® when participants were at rest (estimated hourly metabolic rate around 115 Watts) in that person-work hour. Unshown percentage of hours fell into continuous work category. The percentage of person-work hours in Continuous work is 55.8%±2.3% for WBGT(personal) and 87.9%±1.92% for WBGT(WS)(P-value<0.0001). Statistical significance symbols: '***' denotes P-value of 0 - 0.001, '*' denotes P-value of 0.01 - 0.05, ' ' denotes P-value >0.05 and no significant difference.at different hours.*

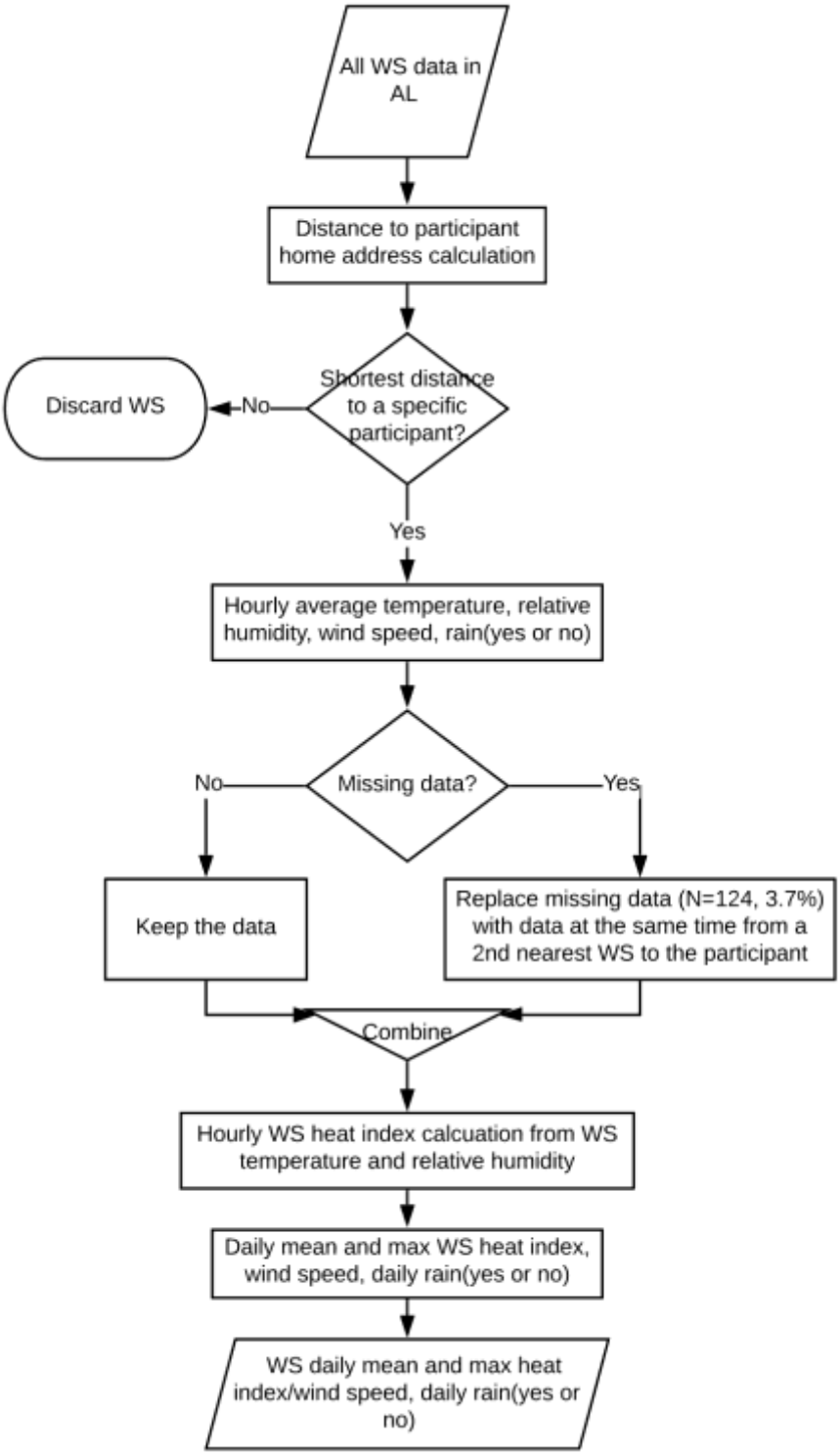


*Appendix Figure 8 Mean difference between WBGT(personal) and WBGT(WS) in percentage of person-work hours of that exceeds weight adjusted TLV® across all participants(Mean difference±95% Confidence Interval). Complete series does not have upper outliers removal. Indoor_Outdoor_Outliers_Removal series have upper outliers removed in both indoor and outdoor conditions. Outdoor_Outliers_Removal series have upper outliers removed in outdoor conditions only. Three participants were identified with more than 15% temperature measurements from personal thermometers as upper outliers. Outleirs_Extreme_Participants_Removal series have these three participants as well as upper outliers in outdoor conditions across all participants removed. Statistical significance symbols: '***' denotes P-value of 0 - 0.001, ' ' denotes P-value >0.05 and no significant difference.*

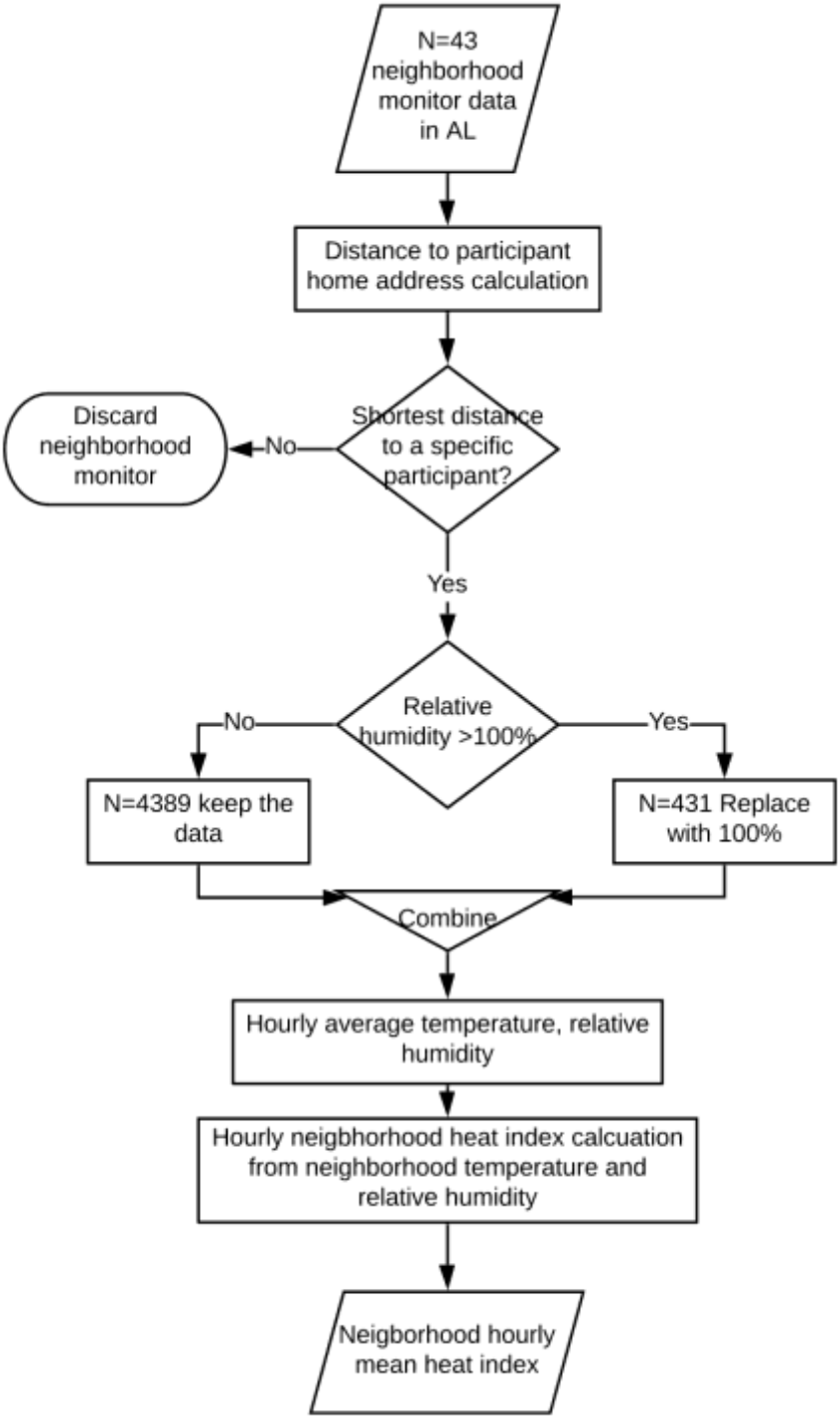


Appendix Figure 9 Mean difference between WBGT(personal) and WBGT(WS) in percentage of person-work hours across all participants(Mean difference±95% Confidence Interval) in different recommended work-rest schedule. Complete series does not have upper outliers removal. Indoor_Outdoor_Outliers_Removal series have upper outliers removed in both indoor and outdoor conditions. Outdoor_Outliers_Removal series have upper outliers removed in outdoor conditions only. Three participants were identified with more than 15% temperature measurements from personal thermometers as upper outliers. Outleirs_Extreme_Participants_Removal series have these three participants as well as upper outliers in outdoor conditions across all participants removed. Statistical significance symbols: ' ' denotes P-value >0.05 and no significant difference.

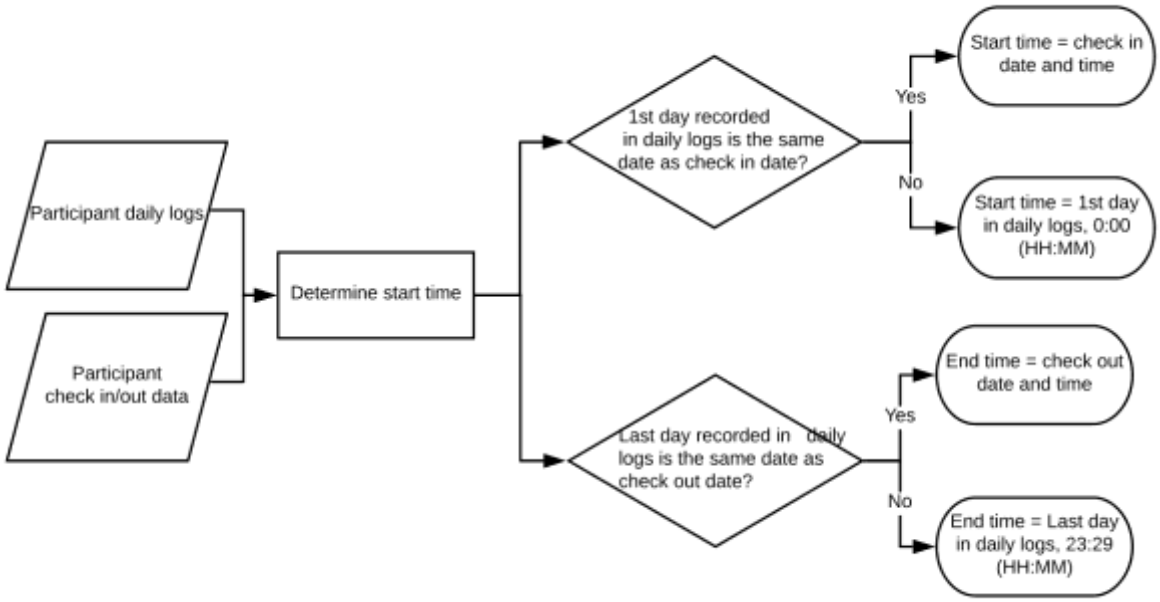
Appendix B Supplemental Materials to Manuscript 2



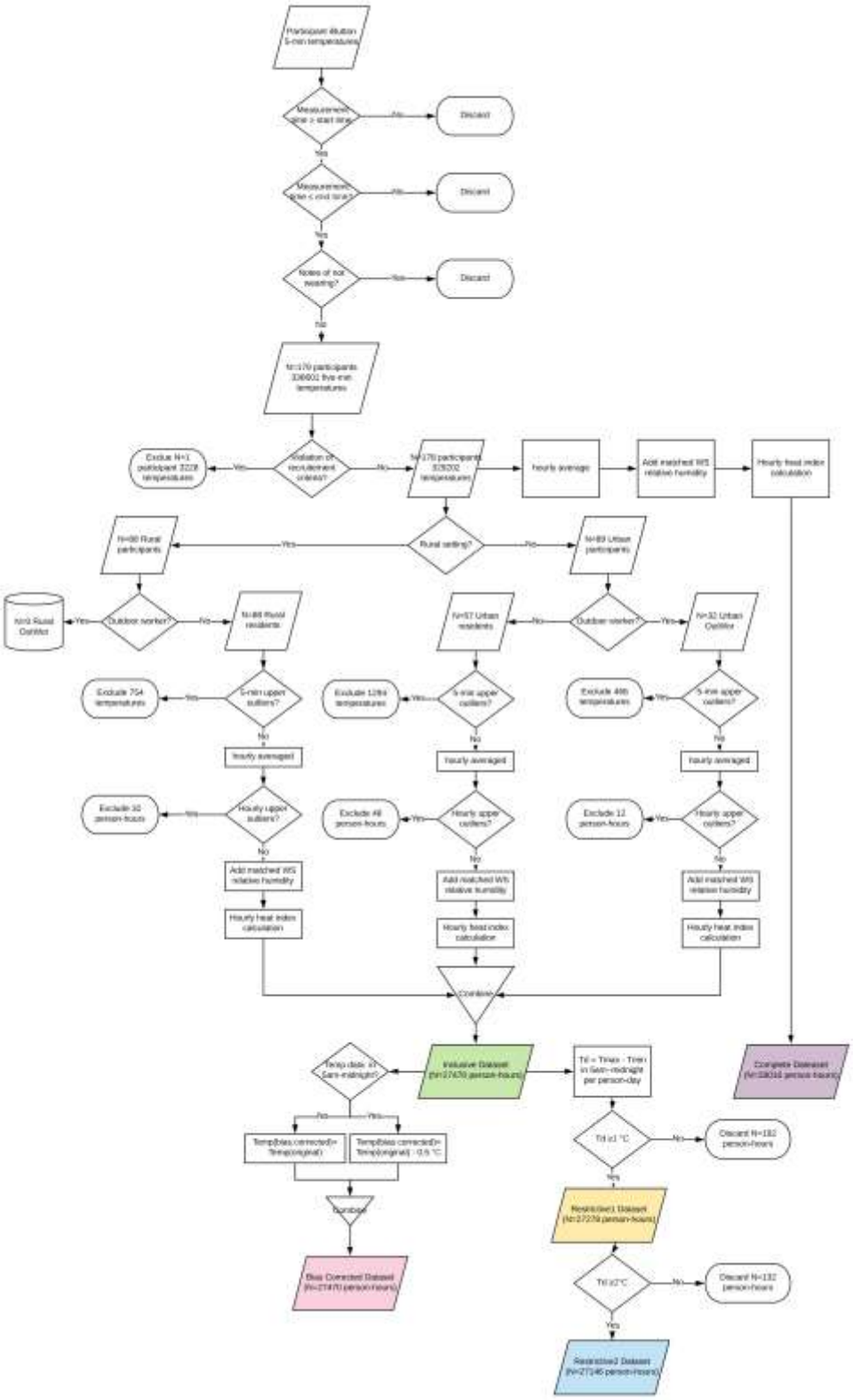
Appendix Figure 10 WS data processing flowchart. pdf



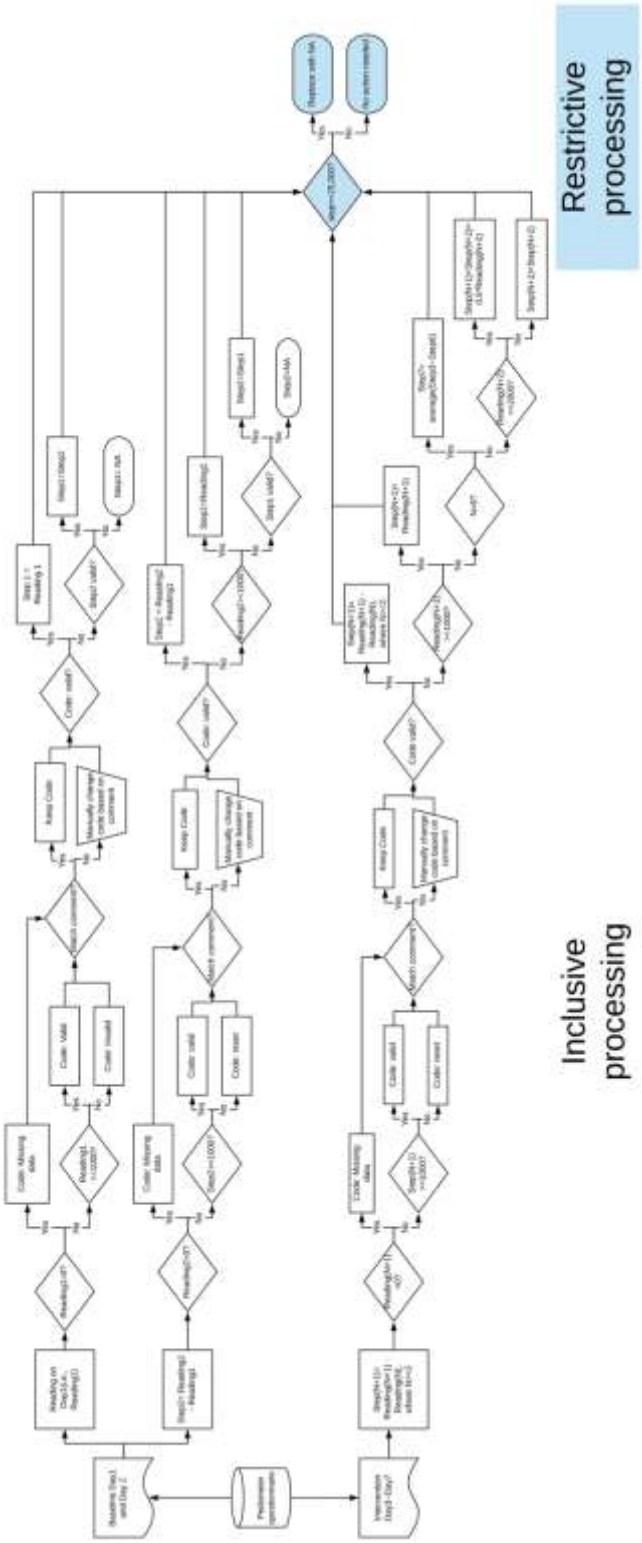
Appendix Figure 11 Neighborhood monitors data processing flowchart. pdf



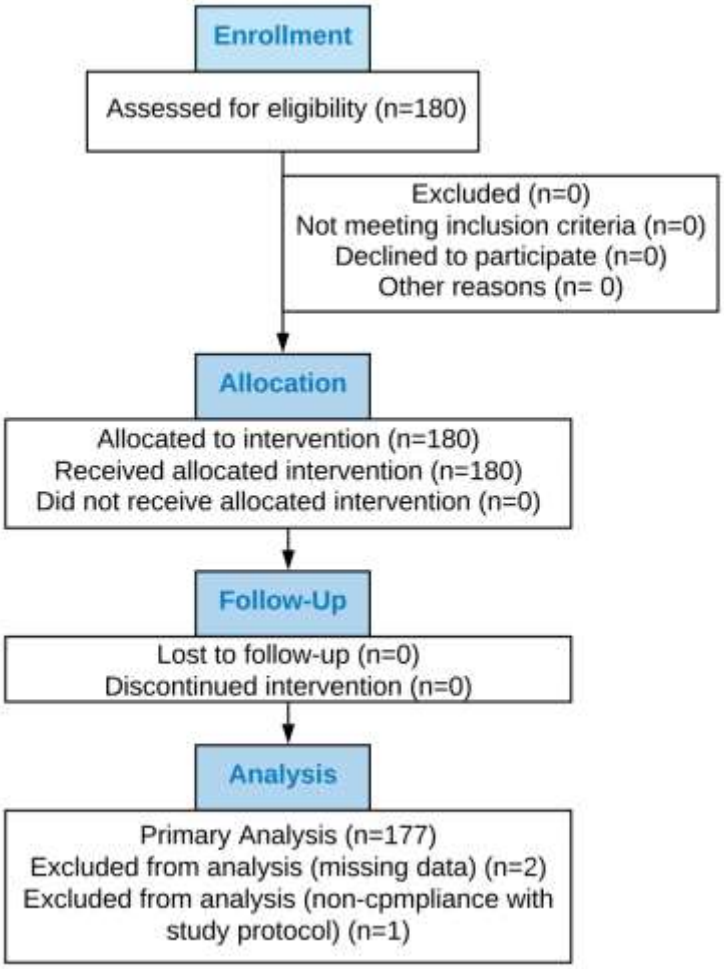
Appendix Figure 12 Decision tree for start and end time of valid study period for each participant



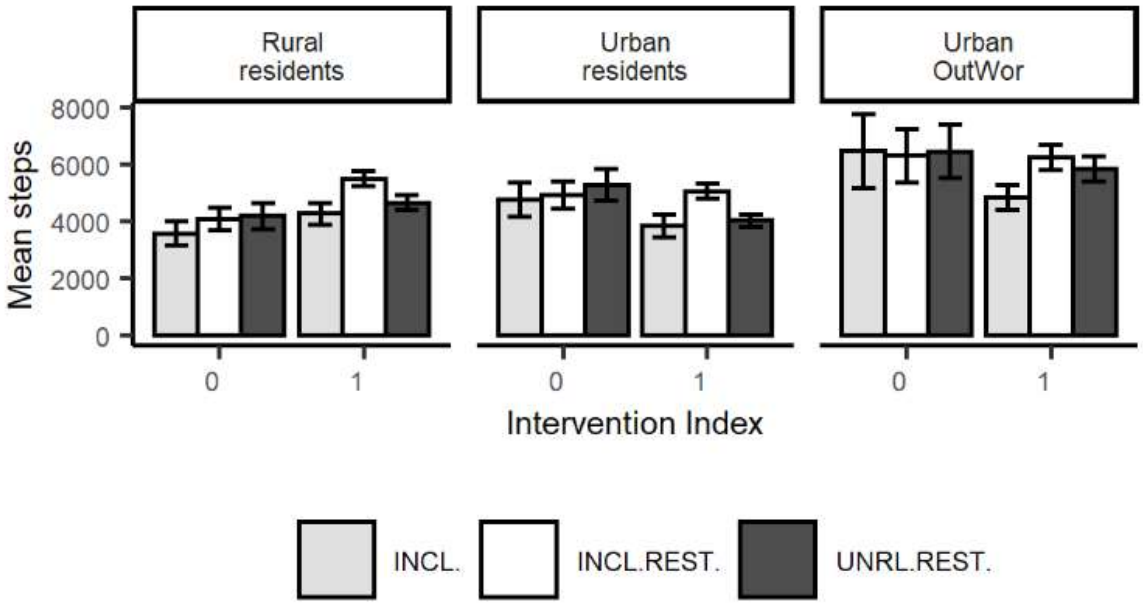
Appendix Figure 13 Thresholds used in creating the Complete, Inclusive, Restrictive1 and Restrictive2 datasets



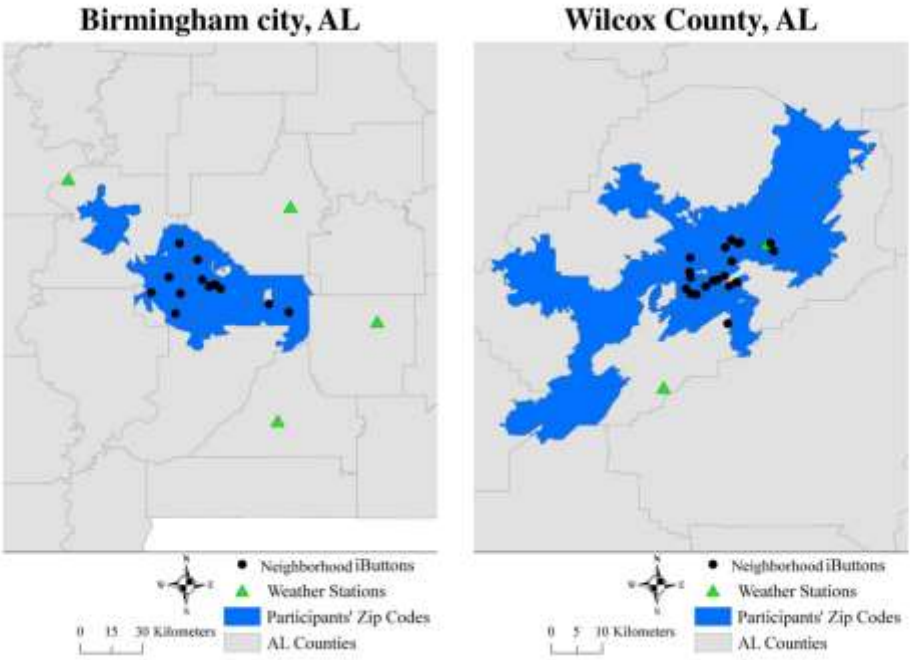
Appendix Figure 14 Pedometer data processing decision tree



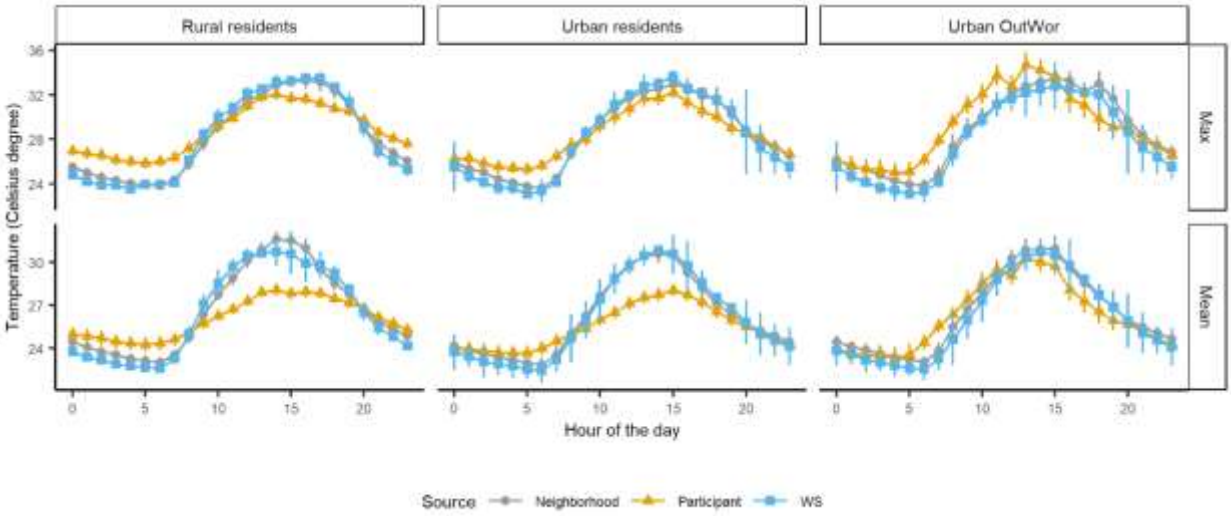
Appendix Figure 15 Participant consort flow chart



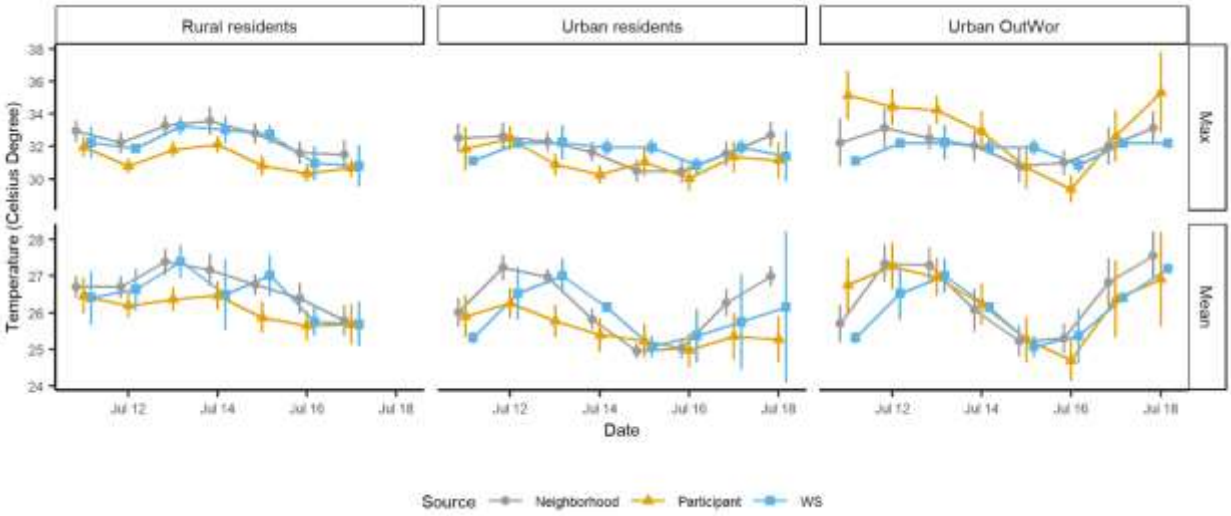
Appendix Figure 16 Effect of pedometer reading data processing methods on daily step estimation. Inclusive (INCL.) method replaced negative steps with NA and includes readings below 1000 and above 25,000. Unrealistic restrictive (UNRL.REST.) removes readings <1000 or ⩾25000. Inclusive +Restrictive (INCL.REST.) uses imputation to replace missing daily steps by following the decision tree.



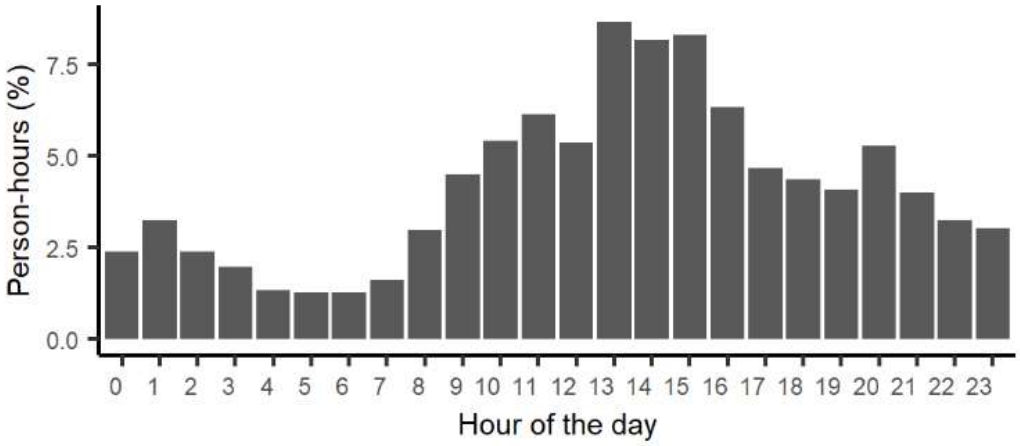
Appendix Figure 17 Geographic locations of matched neighborhood iButtons and WSs, and zip code level area of participant residence in Birmingham city and Wilcox County, AL. pdf



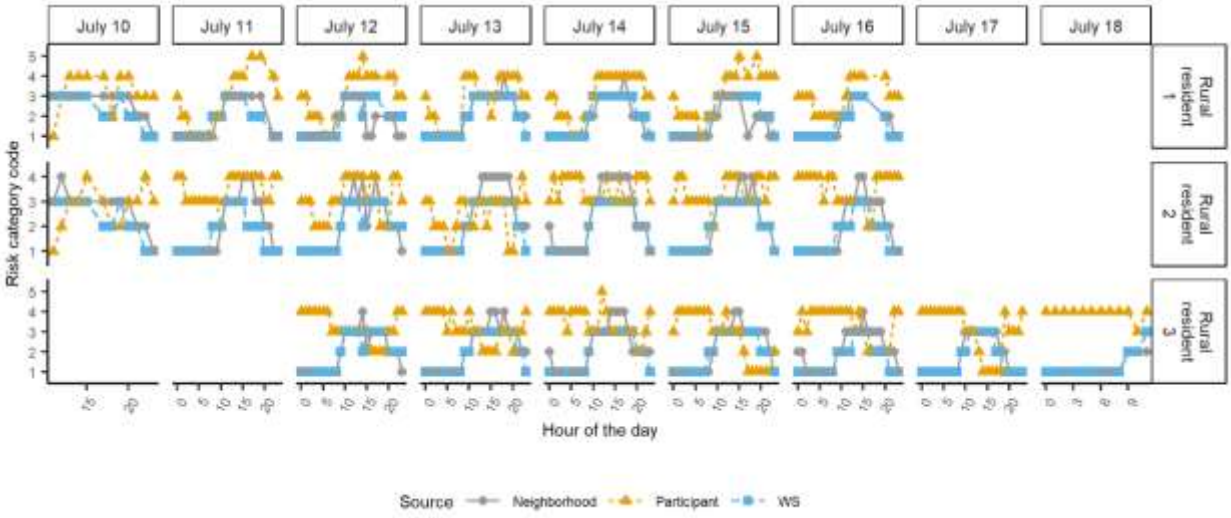
Appendix Figure 18 Diurnal pattern of temperatures in Rural residents (participant N88, neighborhood iButton N=13 , WS N=4), Urban residents (participant N=57, neighborhood iButton N=18 , WS N=2), Urban OutWor (participant N=32, neighborhood iButton N=11 , WS N=2). The 95% confidence intervals were shown. tiff



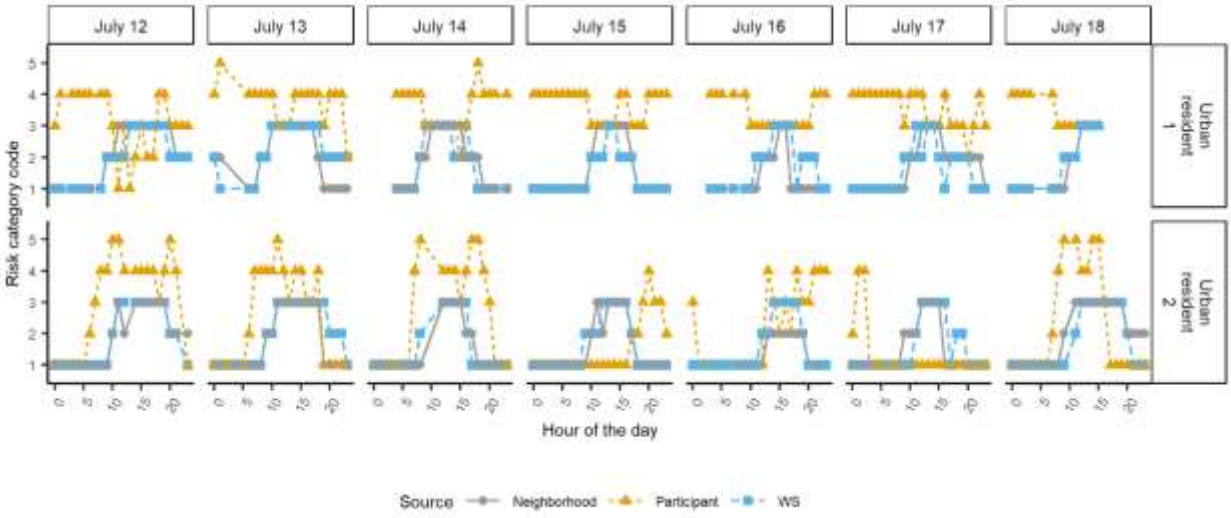
Appendix Figure 19 Date pattern of temperatures in Rural residents (participant N=88, neighborhood iButton N=13 , WS N=4), Urban residents (participant N=57, neighborhood iButton N=18 , WS N=2), and Urban OutWor (participant N=32, neighborhood iButton N=11 , WS N=2). The 95% confidence intervals were shown. tiff



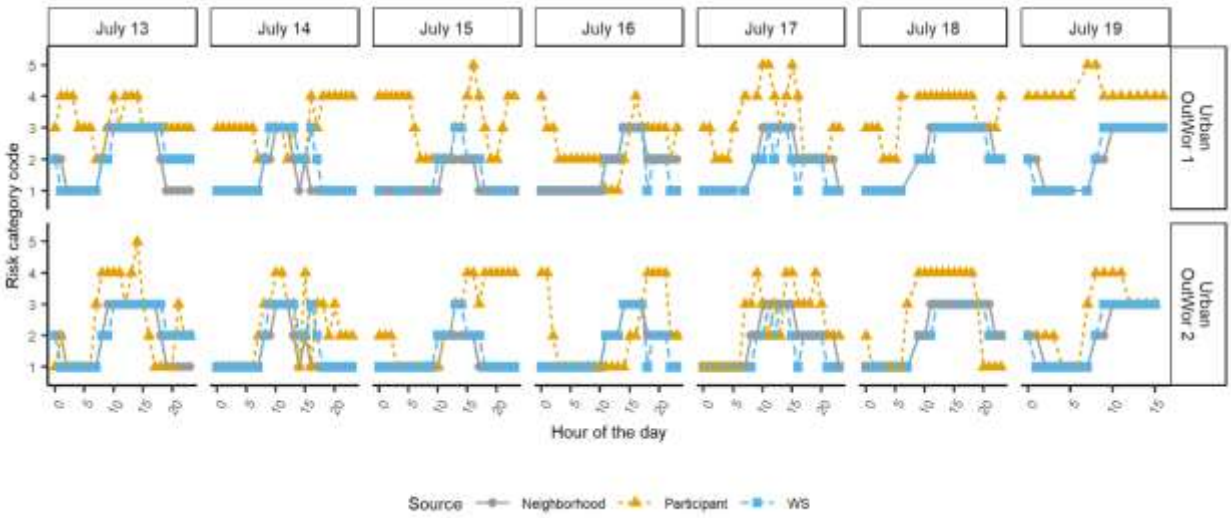
Appendix Figure 20 Hour distribution of the person-hours in Danger and Extreme danger risks of HI[participant]. Person-hours (%) =the number of person-hours in Danger and Extreme danger risks at each hour/ a total of 1 420 person-hours×100%. tiff



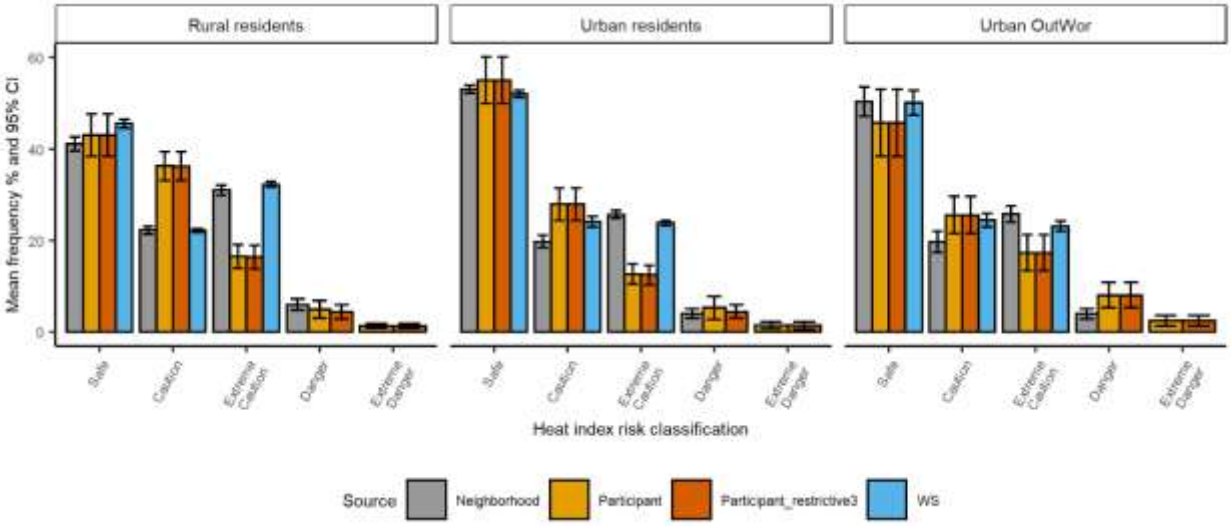
Appendix Figure 21 Time-series analysis of Rural residents with ⩾40 person-hours in Danger and Extreme danger risks. Risk category code 1 = Safe, 2 = Caution, 3 = Extreme caution, 4 = Danger, and 5 = Extreme danger. tiff



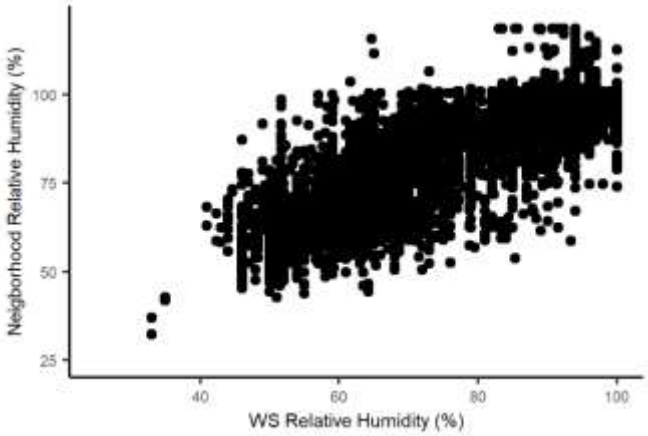
Appendix Figure 22 Time-series analysis of Urban residents with ⩾40 person-hours in Danger and Extreme danger risks. Risk category code 1 = Safe, 2 = Caution, 3 = Extreme caution, 4 = Danger, and 5 = Extreme danger. tiff



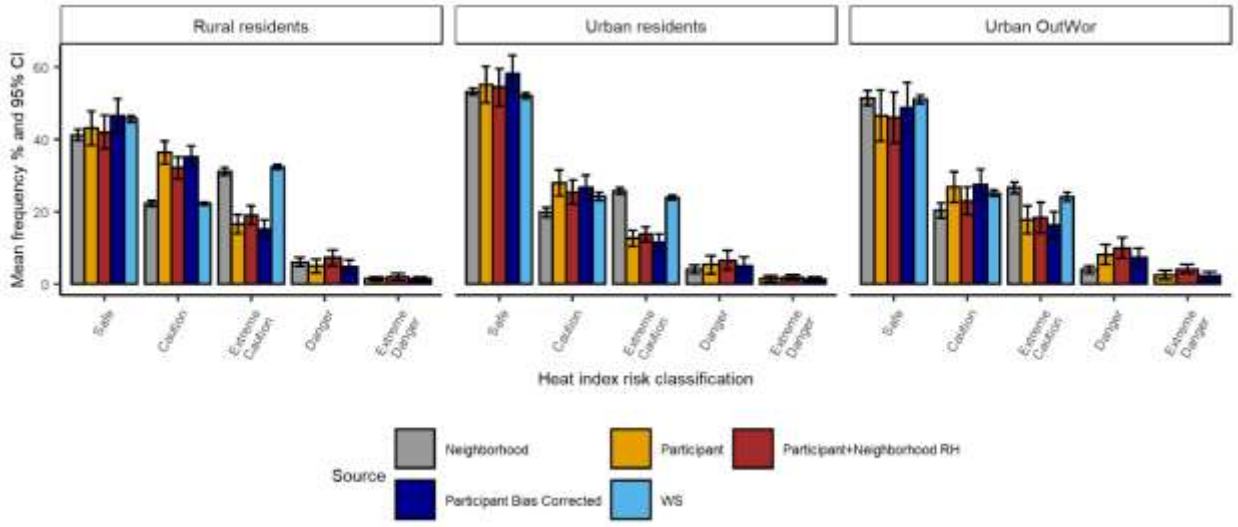
Appendix Figure 23 Time-series analysis of Urban OutWor participants with ⩾40 person-hours in Danger and Extreme danger risks. Risk category code 1 = Safe, 2 = Caution, 3 = Extreme caution, 4 = Danger, and 5 = Extreme danger. tiff



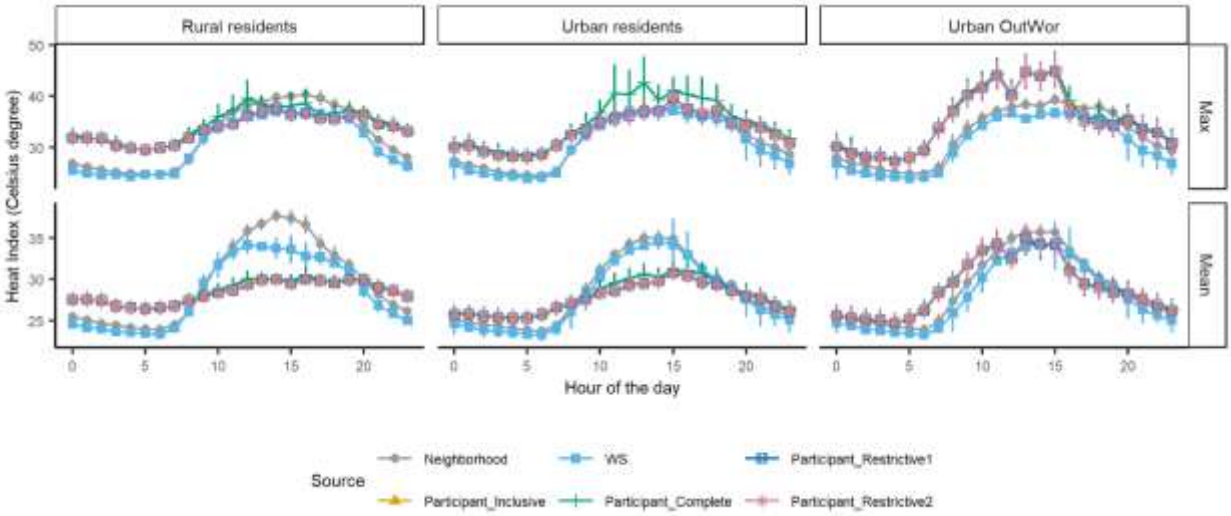
Appendix Figure 24 Mean frequency % of HI risk classification in Rural participants (N=88), Urban participants (N=57), and OutWor (N=32). The 95% confidence intervals were shown. tiff



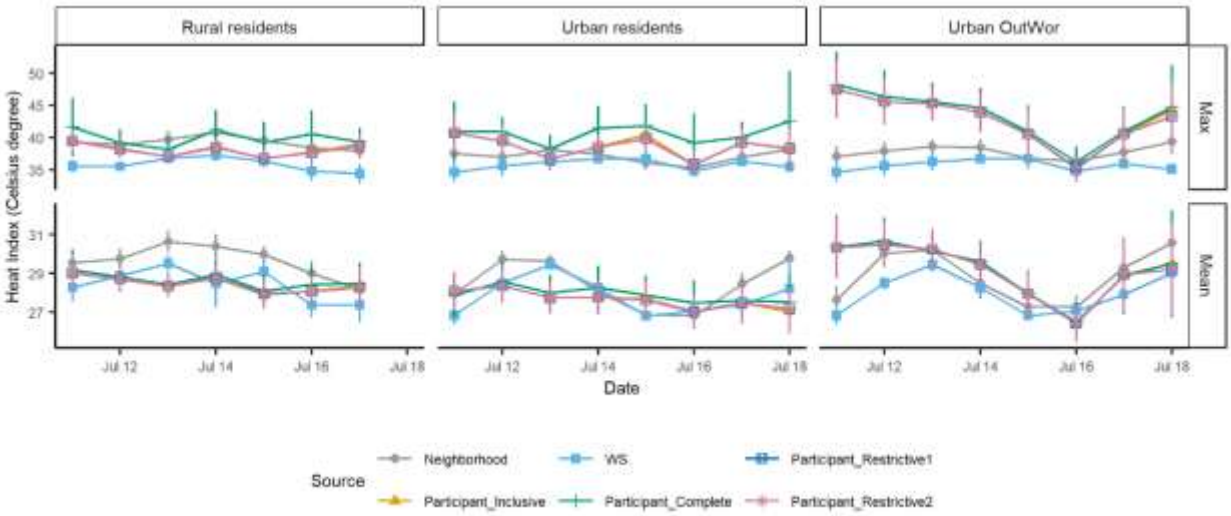
Appendix Figure 25 Scatter plots of relative humidity (%) from WS and neighborhood monitors. tiff



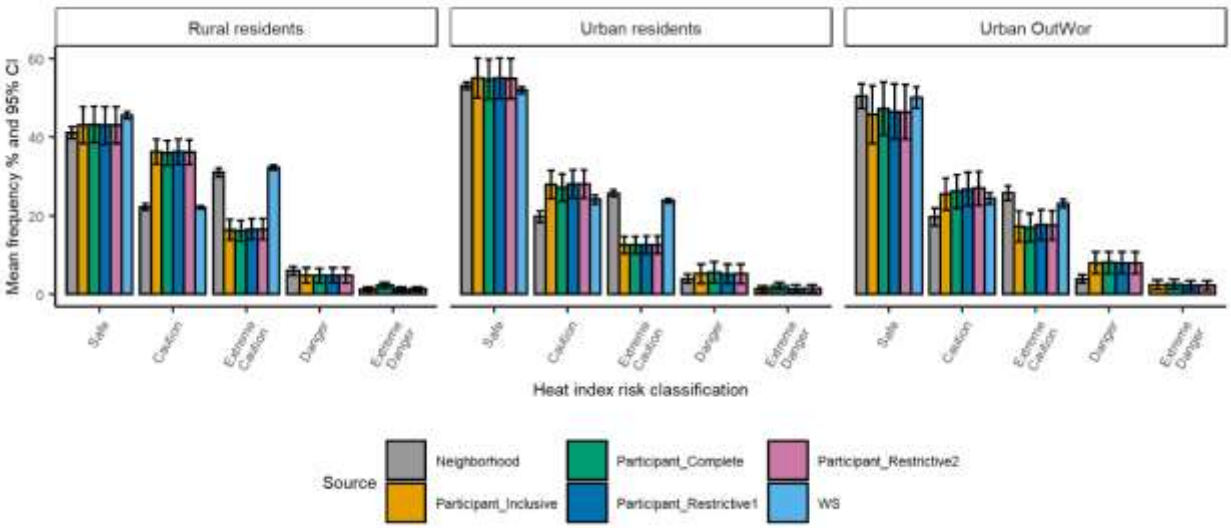
Appendix Figure 26 Mean frequency % of HI risk classification in Rural participants (N=88), Urban participants (N=57), and OutWor (N=32). The 95% confidence intervals were shown. tiff



Appendix Figure 27 Diurnal pattern of heat indexes in Rural residents (participant N=88, neighborhood iButton N=13 , WS N=4), Urban residents (participant N=57, neighborhood iButton N=18 , WS N=2), and Urban OutWor (participant N=32, neighborhood iButton N=11 , WS N=2) in different datasets. The 95% confidence intervals were shown. tiff



Appendix Figure 28 Date pattern of heat indexes experienced in Rural participants (participant N=88, neighborhood iButton N=13 , WS N=4), Urban participants (participant N=57, neighborhood iButton N=18 , WS N=2), Urban OutWor (participant N=32, neighborhood iButton N=11 , WS N=2) in different datasets. The 95% confidence intervals were shown. tiff



Appendix Figure 29 Mean frequency % of HI risk classification in Rural residents (N=88), Urban residents (N=57), and Urban OutWor (N=32). The 95% confidence intervals were shown. Tiff

Appendix Table 2 Linear mixed model fixed effect predictors of individually experienced temperatures in 24 hours.

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	124753.2	59132.5	40395	24161.3
HI[WS] only AIC	125046	59251.7	40479.2	24187.8
HI[neighborhood] only AIC	124781.5	59139.6	40401.4	24247.5
Model pick	Both	Both	Both	Both
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	16.45 (11.50, 21.39)	17.89 (10.37, 25.42)	14.75 (6.47, 23.04)	7.30 (-2.67, 17.25)
Temperature[neighborhood] (°C)	0.20 (0.18, 0.22)*	0.17 (0.14, 0.20)*	0.19 (0.15, 0.23)*	0.17 (0.11, 0.23)*
Temperature [WS] (°C)	0.11 (0.07, 0.14)*	0.09 (0.03, 0.15)*	0.09 (0.03, 0.16)*	0.45 (0.36, 0.54)*
Age	0.01 (-0.01, 0.03)	0.01 (-0.02, 0.03)	0.02 (-0.01, 0.05)	-0.01 (-0.06, 0.04)
Education ≥high school	-0.10 (-0.56, 0.35)	-0.38 (-1.07, 0.31)	0.04 (-0.75, 0.84)	0.51 (-0.36, 1.39)
Annual household income ≥$20K	-0.30 (-0.80, 0.20)	-0.06 (-0.83, 0.71)	-0.09 (-1.01, 0.83)	-0.77 (-1.77, 0.24)
Weekend	-0.31 (-0.39, -0.24)*	-0.25 (-0.35, -0.15)*	0.04 (-0.09, 0.17)	-0.92 (-1.12, -0.72)*
Body fat (%)	-0.02 (-0.06, 0.02)	0.02 (-0.04, 0.08)	-0.04 (-0.10, 0.03)	-0.06 (-0.12, -0.0003)*
Non-rest time (5am~midnight)	0.70 (0.61, 0.78)*	0.32 (0.20, 0.44)*	0.73 (0.59, 0.87)*	1.42 (1.21, 1.62)*
WS relative humidity (%)	-0.02 (-0.03, -0.01)*	-0.02 (-0.03, -0.01)*	-0.02 (-0.04, -0.01)*	0.00 (-0.01, 0.02)
WS wind speed (m/s)	0.13 (0.10, 0.15)*	0.15 (0.11, 0.18)*	0.15 (0.11, 0.19)*	0.12 (0.06, 0.18)*
Intervention	-0.13 (-0.21, -0.06)*	-0.18 (-0.28, -0.08)*	-0.04 (-0.17, 0.09)	-0.36 (-0.55, -0.17)*
log(mean daily steps)	0.37 (-0.12, 0.85)	0.20 (-0.51, 0.91)	0.59 (-0.26, 1.43)	0.59 (-0.41, 1.58)
Employed	0.02 (-0.50, 0.54)	-0.37 (-1.09, 0.35)	0.57 (-0.24, 1.39)	NA
Rural resident[a]	0.27 (-0.26, 0.80)	NA	NA	NA
Outdoor worker[a]	0.61 (-0.07, 1.29)	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable.

Appendix Table 3 Linear mixed model fixed effect predictors of individually experienced temperatures in non-rest time (5am-midnight)

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	94859.2	45307.9	30655.7	18300
HI[WS] only AIC	95073.5	45410.1	30714.6	18323
HI[neighborhood] only AIC	94875.1	45316.5	30656.1	18349.4
Model pick	Both	Both	HI[neighborhood] only	Both
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	17.33 (12.52, 22.14)	16.11 (8.88, 23.35)	19.27 (11.64, 26.91)	7.51 (-2.44, 17.43)
Temperature[neighborhood] (°C)	0.19 (0.16, 0.21)*	0.17 (0.14, 0.20)*	0.19 (0.15, 0.23)*	0.18 (0.11, 0.25)*
Temperature[WS] (°C)	0.10 (0.05, 0.15)*	0.12 (0.05, 0.19)*	NA	0.43 (0.31, 0.55)*
Age	0.01 (-0.01, 0.03)	0.01 (-0.02, 0.03)	0.02 (-0.01, 0.05)	-0.01 (-0.05, 0.03)
Education ≥high school	-0.10 (-0.52, 0.33)	-0.30 (-0.94, 0.34)	0.09 (-0.66, 0.84)	0.42 (-0.41, 1.25)
Annual household income ≥$20K	-0.36 (-0.83, 0.11)	-0.12 (-0.83, 0.58)	-0.31 (-1.17, 0.55)	-0.54 (-1.49, 0.42)
Weekend	-0.38 (-0.47, -0.29)*	-0.24 (-0.36, -0.12)*	0.07 (-0.09, 0.23)	-1.34 (-1.59, -1.10)*
Body fat (%)	-0.03 (-0.06, 0.01)	0.02 (-0.03, 0.07)	-0.04 (-0.11, 0.02)	-0.07 (-0.12, -0.01)*
WS relative humidity (%)	-0.03 (-0.04, -0.02)*	-0.01 (-0.03, 0.003)	-0.04 (-0.05, -0.03)*	0.00 (-0.02, 0.02)
WS wind speed (m/s)	0.15 (0.12, 0.17)*	0.15 (0.11, 0.19)*	0.17 (0.12, 0.22)*	0.14 (0.07, 0.21)*
Intervention	-0.19 (-0.28, -0.10)*	-0.22 (-0.34, -0.10)*	-0.11 (-0.26, 0.05)	-0.38 (-0.61, -0.15)*
log(mean daily steps)	0.48 (0.03, 0.93)*	0.31 (-0.34, 0.96)	0.63 (-0.16, 1.42)	0.81 (-0.13, 1.75)
Employed	0.13 (-0.36, 0.61)	-0.36 (-1.02, 0.30)	0.83 (0.07, 1.59)*	NA
Rural resident[a]	0.14 (-0.35, 0.63)	NA	NA	NA
Outdoor worker[a]	0.91 (0.27, 1.54)*	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in Temperature[WS] indicated that Temperature[WS] was not included in model selection based on AIC.

Appendix Table 4 Linear mixed model fixed effect predictors of individually experienced temperatures in rest time (midnight-5am)

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	25667.5	12240.7	8448.3	4966.3
HI[WS] only AIC	25694.4	12265.4	8449.2	4964.5
HI[neighborhood] only AIC	25667.5	12238.9	8450.3	4970.7
Model pick	Both	HI[Neighborhood] only	Both	HI[WS] only
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	18.75 (11.46, 26.04)	22.02 (11.05, 33.00)	14.75 (2.25, 27.25)	21.10 (5.58, 36.61)
Temperature[neighborhood] (°C)	0.17 (0.11, 0.23)*	0.23 (0.14, 0.31)*	0.10 (-0.01, 0.22)	NA
Temperature[WS] (°C)	0.05 (-0.02, 0.11)	NA	0.12 (0.002, 0.23)*	0.25 (0.14, 0.37)*
Age	0.01 (-0.02, 0.04)	0.01 (-0.03, 0.04)	0.02 (-0.02, 0.07)	-0.01 (-0.09, 0.06)
Education ≥high school	-0.12 (-0.80, 0.56)	-0.62 (-1.65, 0.40)	-0.10 (-1.33, 1.12)	0.78 (-0.62, 2.19)
Annual household income ≥$20K	-0.16 (-0.90, 0.59)	0.09 (-1.05, 1.23)	0.55 (-0.86, 1.95)	-1.50 (-3.11, 0.11)
Weekend	-0.12 (-0.21, -0.03)*	-0.26 (-0.39, -0.13)*	-0.06 (-0.23, 0.10)	0.07 (-0.15, 0.30)
Body fat (%)	0.00 (-0.06, 0.05)	0.03 (-0.06, 0.12)	-0.02 (-0.12, 0.08)	-0.04 (-0.13, 0.06)
WS relative humidity (%)	-0.01 (-0.01, 0.004)	-0.04 (-0.05, -0.02)*	0.00 (-0.01, 0.02)	0.00 (-0.02, 0.02)
WS wind speed (m/s)	0.04 (-0.02, 0.09)	0.13 (0.03, 0.24)*	-0.06 (-0.13, 0.02)	-0.02 (-0.12, 0.08)
Intervention	0.01 (-0.08, 0.11)	-0.08 (-0.23, 0.07)	0.08 (-0.08, 0.25)	-0.06 (-0.29, 0.18)
log(mean daily steps)	0.06 (-0.66, 0.79)	-0.07 (-1.12, 0.99)	0.41 (-0.88, 1.71)	-0.07 (-1.66, 1.52)
Employed	-0.26 (-1.04, 0.52)	-0.35 (-1.42, 0.72)	-0.18 (-1.43, 1.07)	NA
Rural resident[a]	0.61 (-0.18, 1.40)	NA	NA	NA
Outdoor worker[a]	-0.22 (-1.23, 0.80)	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in Temperature[WS] or Temperature[neighborhood] indicated that Temperature[WS] or Temperature[neighborhood] was not included in model selection based on AIC.

Appendix Table 5 Bias correction effect on risk classification based of individually experienced HI

HI[individual] data	Bias corrected	Not bias corrected
Person-hours	Number (%)	Number (%)
Safe	13977 (51%)	12871 (47%)
Caution	8471 (31%)	7729 (28%)
Extreme Caution	3828 (14%)	4698 (17%)
Danger	1099 (4%)	1888 (7%)
Extreme Danger	95 (0.3%)	284 (1%)

Appendix Table 6 Linear mixed model fixed effect predictors of individually experienced HI after bias correction in 24 hours

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	158288.8	74927.8	51119.2	30939.3
HI[WS] only AIC	158462.9	75005.2	51172.3	30957.5
HI[neighborhood] only AIC	158289	74947.5	51117.6	30975.8
Model pick	Both	Both	HI[neighborhood] only	Both
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	19.05 (10.41, 27.69)	20.86 (8.05, 33.67)	16.56 (1.40, 31.72)	13.85 (-2.84, 30.57)
HI[neighborhood] (°C)	0.18 (0.15, 0.20)*	0.15 (0.11, 0.18)*	0.16 (0.14, 0.19)*	0.18 (0.10, 0.26)*
HI[WS] (°C)	-0.02 (-0.05, 0.01)	-0.09 (-0.13, -0.05)*	NA	0.29 (0.20, 0.39)*
Age	0.01 (-0.02, 0.04)	-0.01 (-0.05, 0.04)	0.04 (-0.02, 0.09)	-0.01 (-0.09, 0.07)
Education ≥high school	-0.19 (-1.03, 0.64)	-0.68 (-1.93, 0.57)	-0.10 (-1.62, 1.42)	1.06 (-0.49, 2.60)
Annual household income ≥$20K	-0.59 (-1.50, 0.33)	-0.09 (-1.48, 1.29)	-0.26 (-2.02, 1.49)	-1.53 (-3.31, 0.25)
Weekend	-0.55 (-0.69, -0.41)*	-0.31 (-0.49, -0.13)*	-0.02 (-0.26, 0.22)	-1.66 (-2.04, -1.27)*
Body fat (%)	-0.05 (-0.11, 0.02)	0.05 (-0.05, 0.15)	-0.09 (-0.22, 0.03)	-0.14 (-0.25, -0.04)*
Non-rest time (5am~midnight)	1.09 (0.93, 1.25)*	0.42 (0.20, 0.64)*	1.22 (0.96, 1.47)*	2.21 (1.80, 2.63)*
WS wind speed (m/s)	0.23 (0.18, 0.27)*	0.31 (0.24, 0.37)*	0.24 (0.17, 0.32)*	0.19 (0.07, 0.31)*
Intervention	-0.25 (-0.39, -0.11)*	-0.29 (-0.48, -0.10)*	-0.11 (-0.35, 0.12)	-0.66 (-1.03, -0.29)*
log(mean daily steps)	0.64 (-0.25, 1.52)	0.44 (-0.84, 1.72)	0.84 (-0.77, 2.45)	0.84 (-0.91, 2.59)
Employed	-0.09 (-1.04, 0.86)	-0.81 (-2.11, 0.48)	0.83 (-0.73, 2.38)	NA
Rural resident[a]	0.50 (-0.47, 1.47)	NA	NA	NA
Outdoor worker[a]	1.18 (-0.06, 2.43)	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Appendix Table 7 Linear mixed model fixed effect predictors of individually experienced HI after bias correction in non-rest time (5am-midnight)

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	119647.5	56670.8	38573.9	23448.7
HI[WS] only AIC	119794.4	56740	38613.5	23464.5
HI[neighborhood] only AIC	119646.8	56689.9	38572.3	23472.7
Model pick	HI[neighborhood] only	Both	HI[neighborhood] only	Both
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	18.93 (10.83, 27.04)	20.47 (8.76, 32.18)	17.66 (3.34, 31.98)	12.19 (-4.28, 28.71)
HI[neighborhood] (°C)	0.16 (0.14, 0.17)*	0.14 (0.11, 0.18)*	0.16 (0.13, 0.18)*	0.19 (0.10, 0.27)*
HI[WS] (°C)	NA	-0.09 (-0.13, -0.05)*	NA	0.27 (0.17, 0.37)*
Age	0.01 (-0.02, 0.04)	0.00 (-0.04, 0.04)	0.03 (-0.02, 0.08)	-0.02 (-0.10, 0.07)
Education ≥high school	-0.15 (-0.94, 0.63)	-0.47 (-1.61, 0.68)	0.01 (-1.43, 1.44)	0.92 (-0.60, 2.44)
Annual household income ≥$20K	-0.72 (-1.58, 0.14)	-0.17 (-1.44, 1.10)	-0.74 (-2.40, 0.91)	-1.08 (-2.83, 0.69)
Weekend	-0.65 (-0.82, -0.48)*	-0.32 (-0.53, -0.10)*	0.07 (-0.23, 0.37)	-2.34 (-2.82, -1.85)*
Body fat (%)	-0.06 (-0.12, 0.005)	0.04 (-0.05, 0.14)	-0.10 (-0.22, 0.02)	-0.15 (-0.26, -0.05)*
WS wind speed (m/s)	0.27 (0.22, 0.32)*	0.31 (0.24, 0.39)*	0.30 (0.21, 0.39)*	0.21 (0.07, 0.35)*
Intervention	-0.41 (-0.58, -0.24)*	-0.41 (-0.63, -0.19)*	-0.26 (-0.55, 0.03)	-0.85 (-1.31, -0.38)*
log(mean daily steps)	0.84 (0.002, 1.67)*	0.58 (-0.59, 1.75)	0.94 (-0.59, 2.46)	1.44 (-0.29, 3.16)
Employed	0.11 (-0.78, 1.01)	-0.80 (-1.98, 0.39)	1.36 (-0.11, 2.82)	NA
Rural resident[a]	0.20 (-0.72, 1.11)	NA	NA	NA
Outdoor worker[a]	1.65 (0.48, 2.82)*	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Appendix Table 8 Linear mixed model fixed effect predictors of individually experienced HI after bias correction in rest-time (midnight-5am)

Population	All	Rural residents	Urban residents	Urban OutWor
HI[neighborhood], HI[WS] AIC	34925.5	17118.3	11224	6456.1
HI[WS] only AIC	34979.1	17162.3	11228.2	6455.7
HI[neighborhood] only AIC	34925.2	17117.5	11222.1	6456
Model pick	HI[neighborhood] only	HI[neighborhood] only	HI[neighborhood] only	HI[WS] only
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	16.43 (3.22, 29.64)	10.78 (-9.14, 30.68)	15.38 (-8.12, 38.89)	30.26 (4.69, 55.84)
HI[neighborhood] (°C)	0.36 (0.28, 0.44)*	0.51 (0.37, 0.65)*	0.28 (0.15, 0.41)*	NA
HI[WS] (°C)	NA	NA	NA	0.30 (0.15, 0.46)*
Age	0.01 (-0.04, 0.06)	-0.01 (-0.09, 0.06)	0.05 (-0.03, 0.14)	0.01 (-0.11, 0.14)
Education ≥high school	-0.30 (-1.57, 0.97)	-1.35 (-3.26, 0.57)	-0.38 (-2.72, 1.96)	1.44 (-0.91, 3.78)
Annual household income ≥$20K	-0.23 (-1.61, 1.15)	0.07 (-2.04, 2.19)	1.17 (-1.53, 3.86)	-2.90 (-5.59, -0.21)*
Weekend	-0.20 (-0.38, -0.02)*	-0.41 (-0.68, -0.13)*	-0.23 (-0.52, 0.05)	0.16 (-0.22, 0.54)
Body fat (%)	-0.01 (-0.11, 0.09)	0.09 (-0.07, 0.25)	-0.08 (-0.28, 0.11)	-0.11 (-0.27, 0.05)
WS wind speed (m/s)	0.05 (-0.05, 0.15)	0.18 (-0.05, 0.41)	-0.07 (-0.20, 0.06)	-0.06 (-0.24, 0.12)
Intervention	0.17 (-0.01, 0.36)	-0.05 (-0.38, 0.27)	0.46 (0.18, 0.75)*	0.15 (-0.23, 0.54)
log(mean daily steps)	0.12 (-1.23, 1.46)	0.17 (-1.78, 2.13)	0.51 (-1.97, 2.99)	-0.86 (-3.52, 1.80)
Employed	-0.69 (-2.14, 0.75)	-0.83 (-2.81, 1.15)	-0.78 (-3.17, 1.61)	NA
Rural resident[a]	1.22 (-0.25, 2.69)	NA	NA	NA
Outdoor worker[a]	-0.18 (-2.07, 1.71)	NA	NA	NA

Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in HI[WS] or HI[neighborhood] indicated that HI[WS] or HI[neighborhood] was not included in model selection based on AIC.

Appendix Table 9 Linear mixed model fixed effect predictors of individually experienced HI in the Complete, Restrictive1 and Restrictive2 datasets in 24 hours

Source	Complete	Restrictive1	Restrictive2
Population	All	All	All
Person-hours observation N	28016	27278	27146
HI[neighborhood], HI[WS] AIC	170864.9	158661.9	157958.7
HI[WS] only AIC	171046.4	158885.1	158182.1
HI[neighborhood] only AIC	170863.1	158664.1	157961.1
Model pick	HI[neighborhood] only	Both	Both
Fixed effects	β (95% CI)	β (95% CI)	β (95% CI)
Intercept	18.42 (8.95, 27.88)	16.94 (8.06, 25.81)	16.89 (8.03, 25.75)
HI[neighborhood] (°C)	0.22 (0.21, 0.24)*	0.20 (0.18, 0.23)*	0.21 (0.18, 0.23)*
HI[WS] (°C)	NA	0.03 (0.001, 0.06)*	0.03 (0.002, 0.06)*
Age	0.00 (-0.03, 0.04)	0.01 (-0.03, 0.04)	0.01 (-0.03, 0.04)
Education ≥high school	-0.20 (-1.12, 0.72)	-0.17 (-1.03, 0.70)	-0.16 (-1.03, 0.70)
Annual household income ≥$20K	-0.68 (-1.68, 0.33)	-0.58 (-1.52, 0.36)	-0.58 (-1.52, 0.36)
Weekend	-0.51 (-0.68, -0.34)*	-0.46 (-0.61, -0.32)*	-0.45 (-0.60, -0.31)*
Body fat (%)	-0.06 (-0.13, 0.02)	-0.05 (-0.12, 0.02)	-0.05 (-0.12, 0.02)
Non-rest time (5am~midnight)	1.44 (1.25, 1.63)*	1.01 (0.83, 1.19)*	1.02 (0.84, 1.20)*
WS wind speed (m/s)	0.25 (0.19, 0.31)*	0.25 (0.20, 0.30)*	0.25 (0.20, 0.30)*
Intervention	-0.13 (-0.30, 0.05)	-0.28 (-0.43, -0.14)*	-0.29 (-0.43, -0.14)*
log(mean daily steps)	0.58 (-0.40, 1.55)	0.66 (-0.25, 1.57)	0.66 (-0.26, 1.57)
Employed	0.27 (-0.79, 1.34)	0.43 (-0.57, 1.43)	0.42 (-0.58, 1.41)
Rural resident[a]	0.83 (-0.53, 2.20)	1.22 (-0.07, 2.50)	1.21 (-0.07, 2.49)
Outdoor worker[a]	0.09 (-0.95, 1.14)	-0.09 (-1.07, 0.89)	-0.09 (-1.07, 0.89)

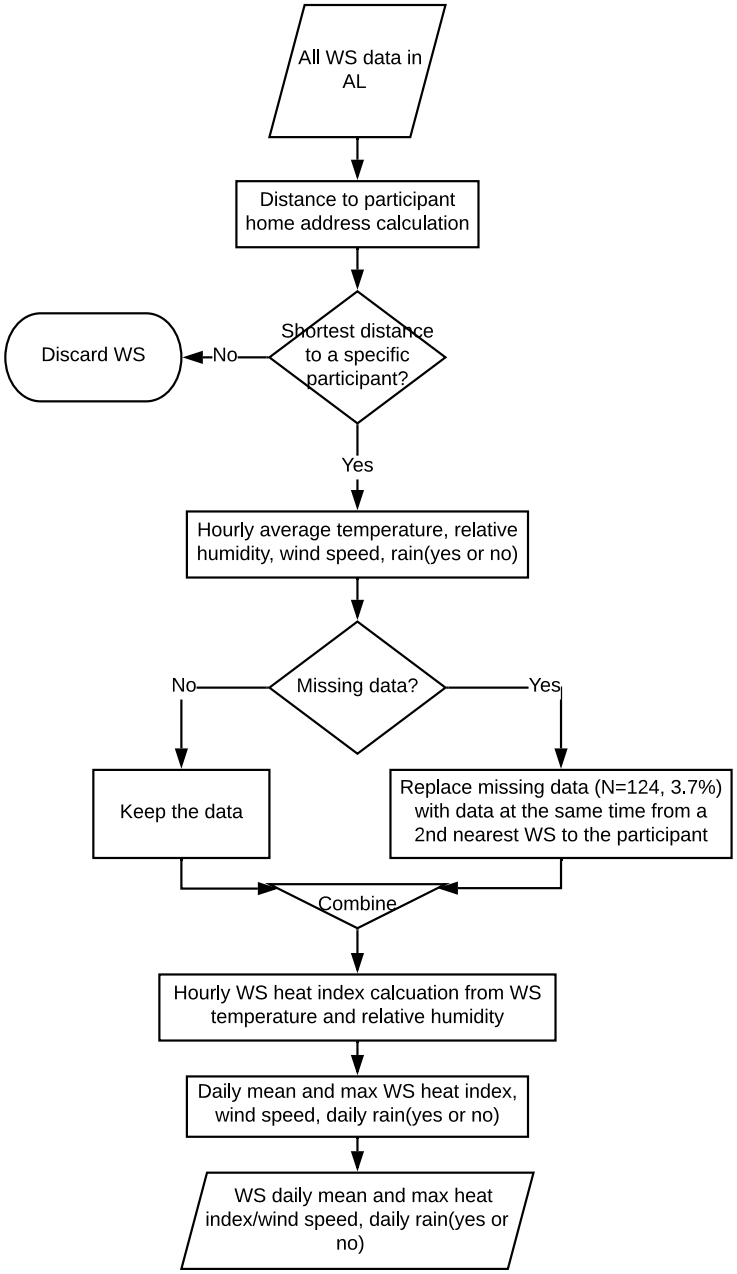
Note: [a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Appendix Table 10 Linear mixed model fixed effect predictors of individually experienced HI in 24 hours where daily steps were calculated without cutoffs <1,000 or ⩾25,000

Population	All	Rural residents	Urban residents	Urban OutWor
Model pick	HI[neighborhood] only	Both	HI[neighborhood] only	Both
Fixed effects	β (95%CI)	β (95%CI)	β (95%CI)	β (95%CI)
Intercept	26.03(20.08, 31.99)	30(22.06, 37.94)	19.34(6.47, 32.21)	16.25(4.44, 28.08)*
HI[neighborhood] (°C)	0.2(0.19, 0.22)*	0.17(0.13, 0.2)*	0.21(0.18, 0.23)*	0.2(0.12, 0.28)*
HI[WS] (°C)	NA	-0.06(-0.1, -0.02)*	NA	0.33(0.23, 0.42)*
Age	0.01(-0.02, 0.05)	0(-0.05, 0.04)	0.04(-0.01, 0.1)	-0.01(-0.09, 0.08)
Education ≥high school	-0.23(-1.1, 0.63)	-0.78(-2.03, 0.47)	-0.21(-1.81, 1.38)	1.02(-0.57, 2.6)
Annual household income ≥$20K	-0.72(-1.66, 0.21)	-0.02(-1.4, 1.37)	-0.38(-2.23, 1.47)	-1.61(-3.43, 0.22).
Weekend	-0.51(-0.65, -0.36)*	-0.29(-0.47, -0.1)*	0.08(-0.17, 0.34)	-1.63(-2.03, -1.23)*
Body fat (%)	-0.07(-0.14, 0)*	0.03(-0.08, 0.13)	-0.1(-0.23, 0.03)	-0.15(-0.26, -0.04)*
Non-rest time (5am-midnight)	1.38(1.22, 1.54)*	0.65(0.42, 0.87)*	1.58(1.31, 1.85)*	2.55(2.12, 2.98)*
WS wind speed (m/s)	0.25(0.2, 0.3)*	0.3(0.23, 0.38)*	0.28(0.2, 0.36)*	0.23(0.11, 0.36)*
Intervention	-0.22(-0.37, -0.08)*	-0.3(-0.5, -0.11)*	0(-0.25, 0.24)	-0.7(-1.09, -0.31)*
log(mean daily steps) from Inclusive (INCL.) without cutoffs	-0.26(-0.82, 0.3)	-0.72(-1.43, -0.02)*	0.39(-0.91, 1.69)	0.46(-0.75, 1.66)
Employed	0.02(-0.96, 1.01)	-0.68(-1.97, 0.62)	0.83(-0.85, 2.5)	NA
Rural resident[a]	0.36(-0.64, 1.37)	NA	NA	NA
Outdoor worker[a]	1.33(0.05, 2.6)*	NA	NA	NA

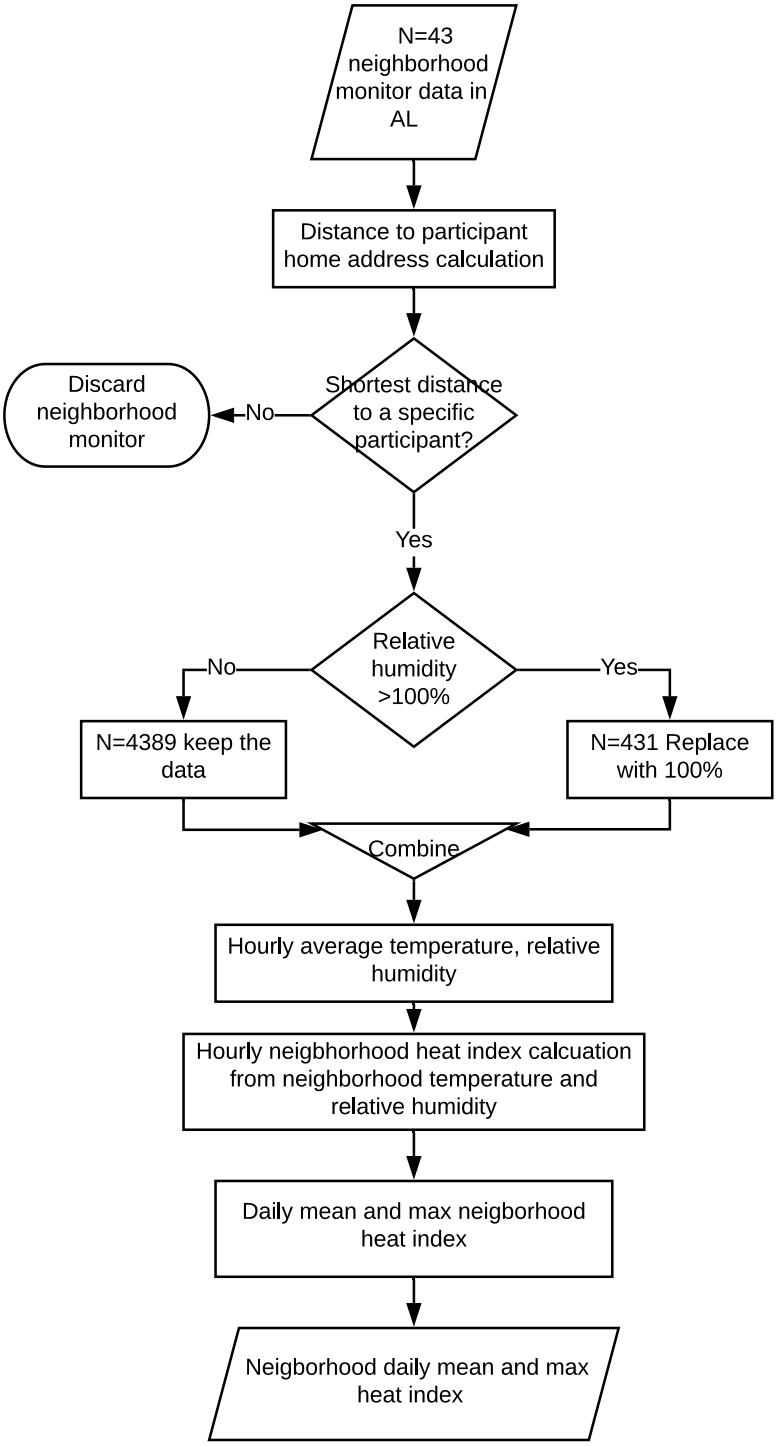
[a]Compared to Urban resident. '*' denotes a β estimates with a 95% confidence interval did not contain 0. NA not applicable. NA in HI[WS] indicated that HI[WS] was not included in model selection based on AIC.

Appendix C Supplemental Materials to Manuscript 3

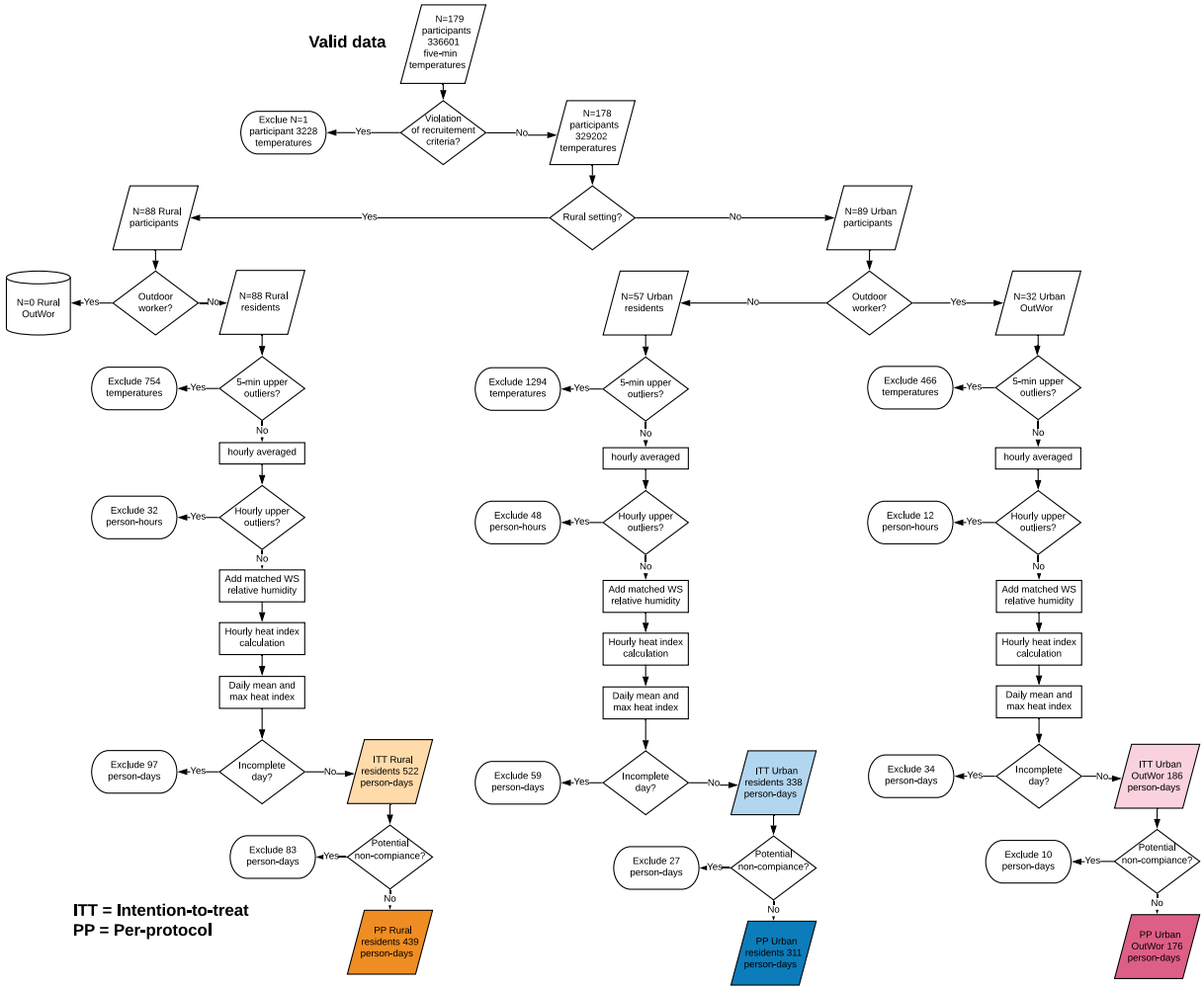


Appendix Figure 30 Data collection and processing flowchart. Bessemer Airport WS and Birmingham International Airport WS were closest to participants' residences in Birmingham while Craig Field WS,

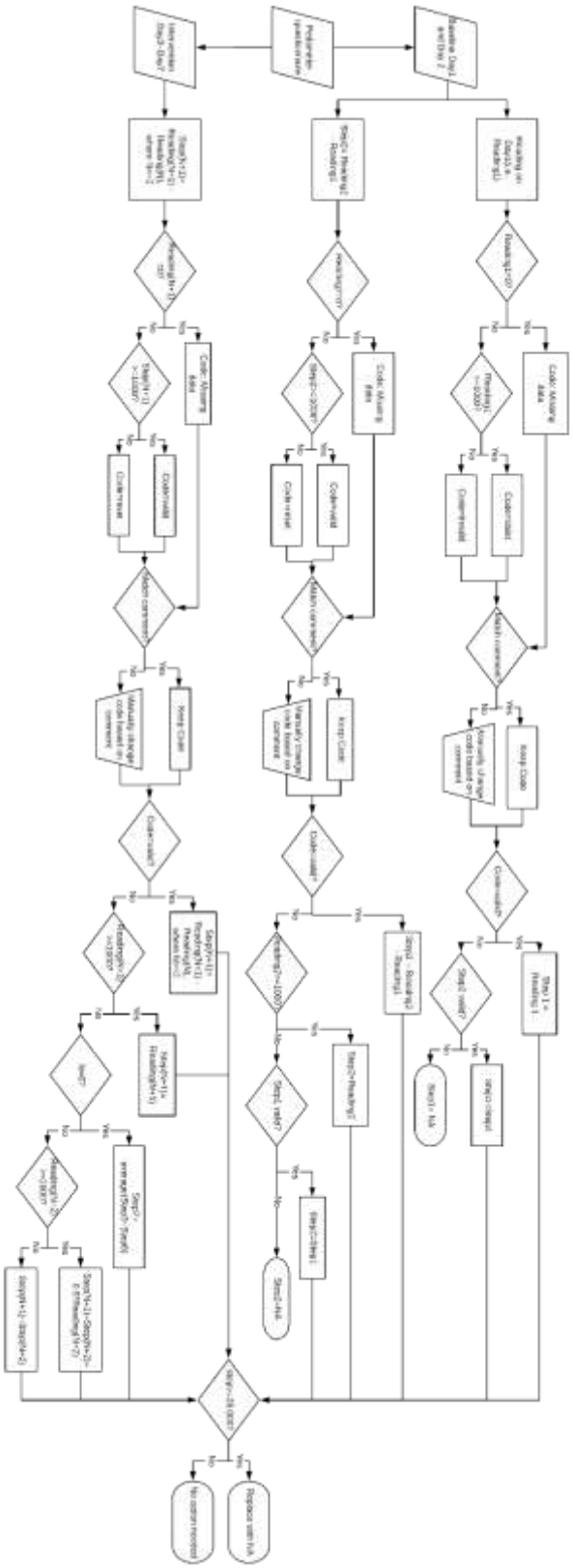
Demopolis Municipal Airport WS, Mac Crenshaw Memorial Airport WS, and Middleton Field Airport WS were closest to participants' residences in Wilcox County.



Appendix Figure 31 Data collection and processing flowchart.



Appendix Figure 32 Data collection and processing flowchart.



Appendix Figure 33 Data collection and processing flowchart.

Appendix Table 11 Body measurement processing record. The body fat, body water, muscle mass changes of five participants considered unrealistic or extreme were excluded (e.g., participants had body fat change ratio of 17-44%). The exclusion effect was examined in sensitivity analysis.

Body measurement category	Participant N with available data	Participant N removed due to unrealistic or extreme body measurement change	Participant N remained in the main results
Weight (lbs.)	177	0	177
Body fat (%)	172	5	167
Body water (%)	172	5	167
Muscle mass (lbs.)	172	5	167

Appendix Table 12 Results of risk difference regression describing the relation between the probability of intervention compliance and ambient conditions, individual-level factors

Fixed effect	β 95% CI in percent (%)
Intercept	-99.73 (-266.22, 66.77)
HI[individual]$_{\text{daily mean}}$ (°C)	0.95 (-0.11, 2.02)
HI[WS]$_{\text{daily mean}}$ (°C)	3.28 (-2.19, 8.75)
HI[neighborhood]$_{\text{daily mean}}$ (°C)	0.3 (-3.84, 4.45)
HI[individual]$_{\text{daily max}}$ (°C)	0.47 (0.01, 0.92)*
HI[WS]$_{\text{daily max}}$ (°C)	0.34 (-3.52, 4.19)
HI[neighborhood]$_{\text{daily max}}$ (°C)	0.07 (-1.90, 2.03)
Wind Spd daily mean (m/s)	4.51 (-6.47, 15.49)
Weekend	2.41 (-4.64, 9.46)
Age	0.17 (-0.09, 0.43)
Education > high school	5.02 (-2.3, 12.35)
Annual household income >20k	2.36 (-5.52, 10.24)
Rural residents[a]	6.4 (-3.92, 16.71)
Urban OutWor[a]	8.75 (-1.7, 19.2)
Body fat (%)	-0.53 (-1.13, 0.08)
Diabetic	-6.9 (-16.2, 2.39)
Health condition in Fair[b]	-6.37 (-17.2, 4.46)
Health condition in Poor[b]	-0.18 (-15.23, 14.87)
Godin Inactivity	-15.70 (-22.46, -8.94)*
Log(daily steps)	3.43 (-0.38, 7.23)
Rain	9.1 (1.5, 16.71)*

Note: '*' indicates a 95% confidence interval does not contain 0.
[a]Compared to Urban participants
[b]Compared to health condition in Good

Appendix Table 13 Results of the linear mixed models describing the relation of the intervention and daily pedometer steps with an interaction term between intervention and groups in Intent-to-Treat (ITT).

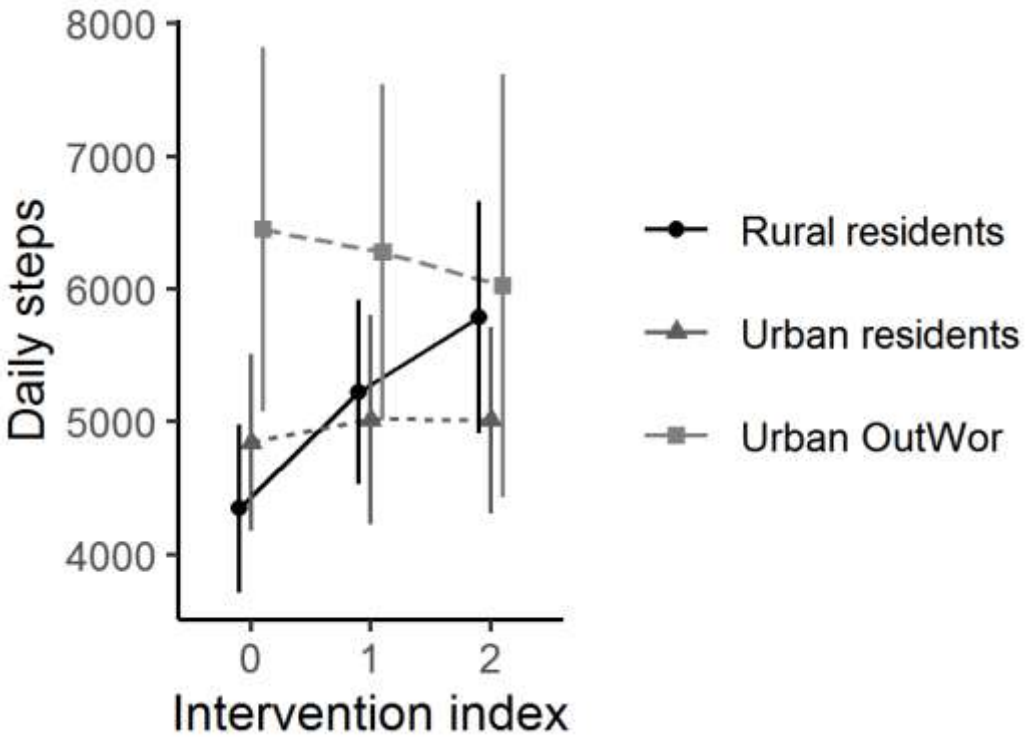
Population	All
Fixed effects	β 95%CI
Intercept	11415 (1164, 21667)
WS HI Max(°C)	-164 (-494, 167)
Neighborhood HI Max(°C)	57 (-117, 231)
WS HI Mean(°C)	-1 (-415, 413)
Neighborhood HI Mean(°C)	-2 (-353, 349)
WS wind speed mean (m/s)	411 (-545, 1367)
WS rain	-493 (-1098, 111)
Age	16 (-13, 44)
Annual household income >20k	-74 (-865, 719)
Education > high school	-130 (-864, 601)
Employed	414 (-406, 1233)
Body fat (%)	-86 (-143, -29)*
Diabetic	329 (-554, 1210)
Godin Inactivity	-199 (-909, 508)
Health condition in Fair[a]	499 (-416, 1408)
Health condition in Poor[a]	316 (-1954, 2586)
Intervention	250 (-697, 1196)
Rural residents	-417 (-1639, 802)
Urban OutWor	1067 (-362, 2498)
Intervention*Rural residents	912 (-321, 2145)
Intervention*Urban OutWor	-325 (-1779, 1128)

Note: '*' denotes a 95% confidence interval does not contain 0. The model for all participants did not include a group factor. Urban resident was the reference group.
[a]Compared to health condition in Good

Appendix Table 14 Intervention &weekdays vs. intervention &weekend effect on daily pedometer steps in ITT.

Model	Group	All	Rural residents	Urban residents	Urban OutWor
1	Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
	Intercept	8968 (-2325, 20246)	1823 (-15505, 19120)	10282 (-15117, 35711)	22308 (-7548, 52197)
	Intervention &weekdays	484 (-128, 1095)	773 (-129, 1675)	152 (-881, 1184)	189 (-1351, 1727)
	Intervention &weekends	886 (190, 1580)*	1428 (464, 2389)*	232 (-1276, 1737)	290 (-1693, 2262)
2	Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
	Intercept	5421 (-10731, 21572)	9596 (-11764, 30964)	2706 (8985, 64397)	5526 (-108772, 120406)
	Weekend	453 (-344, 1250)	318 (-837, 1475)	593 (-1887, 3073)	1423 (-3495, 6292)

Note: '*' denotes a 95% confidence interval does not contain 0. Models for all participants did not include a group factor. Model 2 includes data on intervention days only.



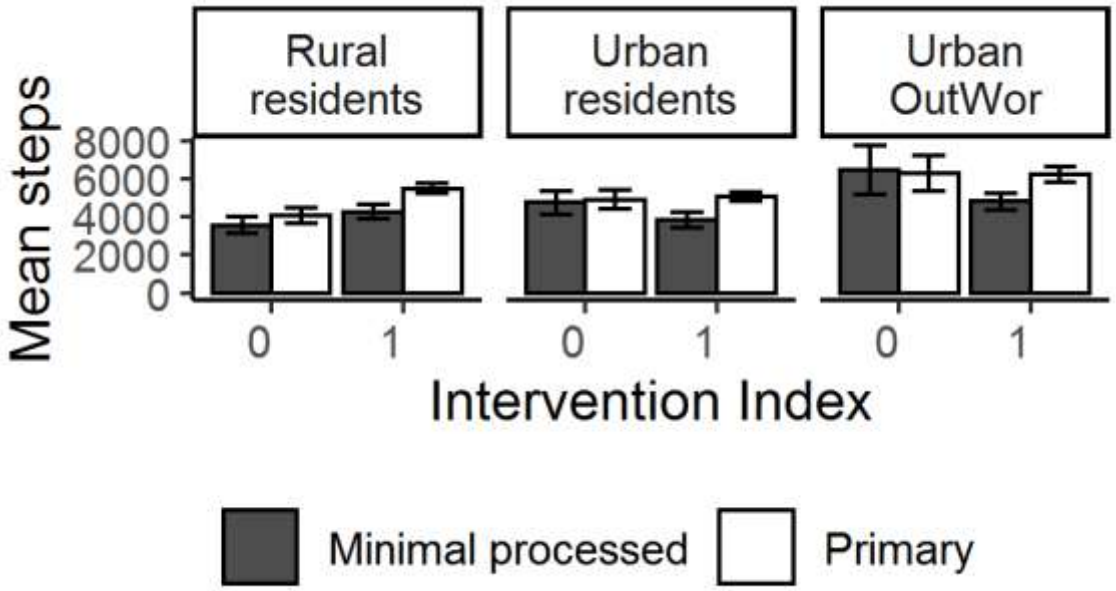
Appendix Figure 34 Intervention &weekdays vs. intervention &weekend effect on daily pedometer steps. The population mean of the individual mean daily steps on baseline days (intervention index = 0), intervention &weekdays (intervention index =1) and intervention &weekend (intervention index = 2) in different population groups. The 95% confidence intervals are shown.

Appendix Table 15 Results of linear mixed models describing the relation between the intervention and the daily pedometer steps in Per-Protocol (PP).

Population	All	Rural residents	Urban residents	Urban OutWor
Fixed effects	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	13143 (2754, 23529)	9727 (-5926, 25378)	5624 (-15840, 27089)	25303 (-146, 50729)
WS HI Max(°C)	-279 (-615, 56)	-76 (-725, 573)	-375 (-977, 227)	-235 (-1164, 694)
Neighborhood HI Max(°C)	31 (-149, 211)	125 (-121, 375)	112 (-210, 433)	-94 (-591, 398)
WS HI Mean(°C)	43 (-392, 479)	100 (-521, 721)	284 (-539, 1107)	-572 (-1986, 845)
Neighborhood HI Mean(°C)	83 (-287, 454)	-237 (-790, 314)	-25 (-736, 685)	523 (-558, 1603)
WS wind speed mean (m/s)	648 (-360, 1656)	100 (-1367, 1555)	1332 (-405, 3068)	599 (-2501, 3701)
WS rain	-185 (-834, 465)	-279 (-1121, 565)	577 (-748, 1902)	-247 (-2494, 1990)
Age	13 (-16, 42)	16 (-21, 54)	13 (-22, 49)	-31 (-172, 111)
Annual household income >20k	-178 (-962, 610)	120 (-963, 1207)	-778 (-2003, 450)	-1133 (-3484, 1227)
Education > high school	-89 (-831, 653)	951 (-63, 1961)	-353 (-1491, 789)	-2486 (-4559, -389)*
Employed	602 (-189, 1392)	201 (-844, 1241)	655 (-379, 1689)	NA
Body fat (%)	-105 (-161, -50)*	-88 (-168, -7)*	-40 (-126, 44)	-116 (-254, 21)
Diabetic	540 (-352, 1426)	60 (-1027, 1135)	337 (-956, 1631)	2977 (-1112, 7026)
Godin Inactivity	-179 (-898, 533)	-1452 (-2466, -442)*	375 (-631, 1375)	2103 (103, 4114)*

Health condition in Fair[a]	468 (-481, 1412)	912 (-348, 2155)	634 (-544, 1814)	-1348 (-4203, 1455)
Health condition in Poor[a]	557 (-1768, 2887)	4116 (703, 7472)*	-2983 (-6177, 223)	-313 (-5544, 4911)
Intervention	579 (5, 1154)*	958 (130, 1786)*	229 (-796, 1255)	57 (-1358, 1471)

Note: '*' denotes a 95% confidence interval does not contain 0. The model for all participants did not include a group factor.
[a]Compared to health condition in Good



Appendix Figure 35 Effect of data processing methods on the pedometer step results. Primary dataset was obtained by following the decision tree in . Minimal processed dataset was obtained by replacing the negative steps with NA. The 95% confidence intervals are shown.

Appendix Table 16 Effect of data processing methods on the pedometer step results. Results of linear mixed models describing the relation between the intervention and the daily pedometer steps processed in minimal processed dataset.

Population	All	Rural residents	Urban residents	Urban OutWor
Fixed effects	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	6540 (-5762, 18838)	-1189 (-19451, 17073)	9597 (-19878,39091)	4085 (-19227,27342)
WS HI Max(°C)	-187 (-587, 213)	594 (-166, 1352)	-146 (-1013,725)	-732 (-1591,125)
Neighborhood HI Max(°C)	28 (-190, 245)	7 (-311, 326)	325 (-132,776)	-52 (-519,416)
WS HI Mean(°C)	607 (91, 1123)*	129 (-602, 861)	1001 (-162,2168)	957 (-346,2257)
Neighborhood HI Mean(°C)	-352 (-783, 78)	-540 (-1206, 121)	-1309 (-2306,-316)*	96 (-863,1055)
WS wind speed mean (m/s)	286 (-886, 1458)	-313 (-1999, 1374)	302 (-2163,2767)	1796 (-992,4572)
WS rain	-122 (-872, 628)	271 (-686, 1227)	-865 (-2710,982)	669 (-1301,2623)
Age	27 (-9, 64)	22 (-29, 73)	49 (-3,101)	-1 (-150,146)
Annual household income >20k	-477 (-1459, 506)	-139 (-1617, 1336)	-1761 (-3562,31)	-1194 (-3654,1303)
Education > high school	-65 (-1000, 867)	-216 (-1595, 1166)	1430 (-283,3166)	-1707 (-3887,472)
Employed	578 (-410, 1569)	163 (-1262, 1595)	1096 (-375,2575)	NA
Body fat (%)	-110 (-180, -40)*	-95 (-207, 17)	-119 (-241,4)	-49 (-190,93)
Diabetic	579 (-527, 1684)	-36 (-1496, 1424)	2550 (574,4495)*	1505 (-2841,5798)

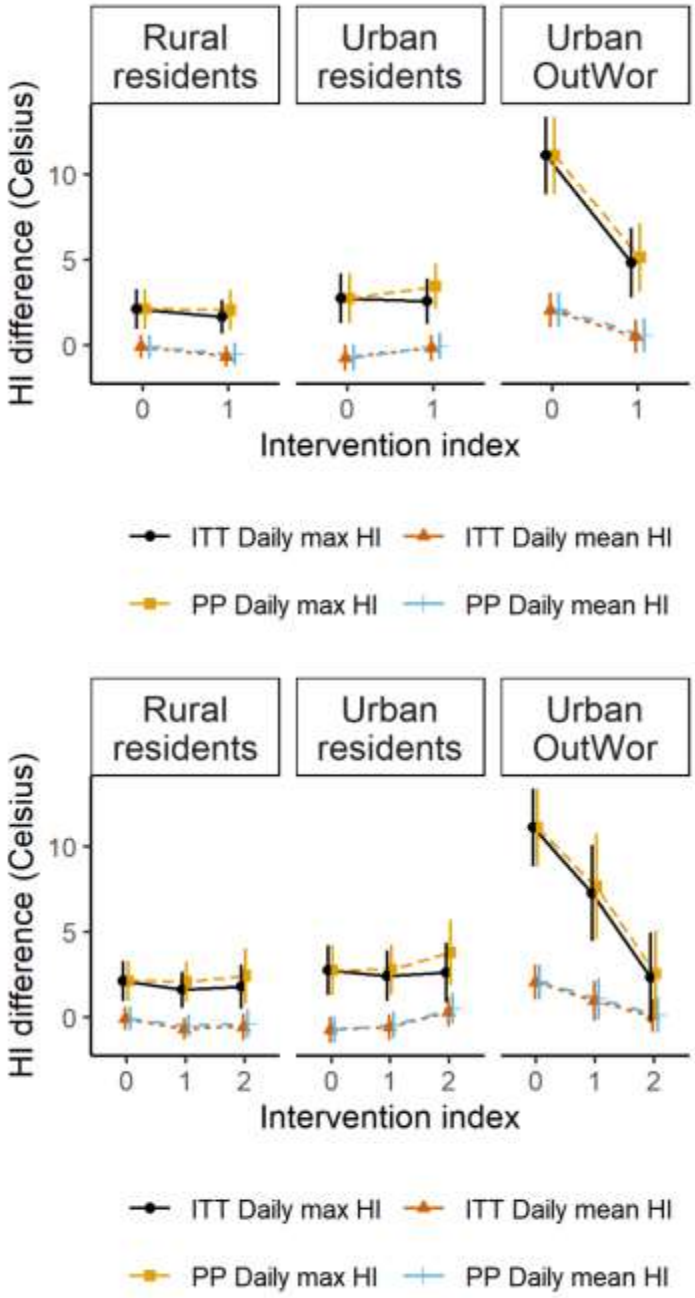
Godin Inactivity	-74 (-976, 827)	-991 (-2383, 392)	254 (-1225,1757)	2121 (25,4219)
Health condition in Fair[a]	-353 (-1516, 809)	-530 (-2210, 1149)	1097 (-640,2854)	-2213 (-5013,584)
Health condition in Poor[a]	1195 (-1833, 4209)	4586 (-291, 9364)	-1973 (-6711,2789)	-103 (-5677,5433)
Intervention	-271 (-960, 418)	427 (-544, 1397)	-972 (-2392,447)	-976 (-2233,276)

Note: '*' denotes a 95% confidence interval does not contain 0. The model for all participants did not include a group factor.
[a]Compared to health condition in Good

Appendix Table 17 Results of linear mixed models describing the relation between the intervention and the daily mean or max heat index experienced by individuals with an interaction term between intervention and groups in ITT.

	Model 1		Model2
Dependent variable	HI[individual] ***Mean***	Dependent variable	HI[individual] ***Max***
Fixed effects	β 95%CI	Fixed effects	β 95%CI
(Intercept)	23.39 (18.03, 28.75)*	Intercept	40.4 (28.47, 52.26)*
Neighborhood Mean HI(°C)	0.22 (0.09, 0.34)*	Neighborhood Max HI(°C)	0.21 (-0.02, 0.43)
WS Mean HI(°C)	NA	WS Max HI(°C)	NA
WS wind speed mean (m/s)	0.68 (0.23, 1.14)*	WS wind speed max (m/s)	0.56 (0.28, 0.83)*
Age	0.02 (-0.01, 0.05)	Age	0.00 (-0.06, 0.06)
Annual household income>20k	-0.64 (-1.6, 0.31)	Annual household income>20k	-0.95 (-2.56, 0.66)
Education > high school	-0.35 (-1.23, 0.53)	Education > high school	-0.68 (-2.16, 0.82)
Body fat (%)	-0.06 (-0.13, 0.01)	Body fat (%)	-0.17 (-0.28, -0.05)*
Log (daily steps)	-0.08 (-0.29, 0.14)	Log (daily steps)	-0.48 (-1.1, 0.15)
Employed	0.13 (-0.86, 1.11)	Employed	0.93 (-0.73, 2.59)
Diabetic	-0.3 (-1.36, 0.76)	Diabetic	-0.72 (-2.51, 1.07)
Health condition in Fair[a]	-0.2 (-1.3, 0.9)	Health condition in Fair[a]	0.12 (-1.73, 1.98)
Health condition in Poor[a]	0.46 (-2.3, 3.22)	Health condition in Poor[a]	-0.05 (-4.68, 4.59)
Godin Inactivity	0.01 (-0.84, 0.86)	Godin Inactivity	-0.36 (-1.8, 1.08)
Intervention	-0.06 (-0.54, 0.42)	Intervention	-0.4 (-1.86, 1.06)
Rural residents	0.73 (-0.38, 1.85)	Rural residents	-0.88 (-3.12, 1.34)
Urban OutWor	2.28 (0.91, 3.65)*	Urban OutWor	7.02 (4.37, 9.68)*
Rain	0.23 (-0.09, 0.54)	Rain	-0.15 (-1.07, 0.77)
Intervention*Rural residents	-0.38 (-1.01, 0.25)	Intervention*Rural residents	0.42 (-1.56, 2.41)
Intervention*Urban OutWor	-1.81 (-2.57, -1.05)*	Intervention*Urban OutWor	-5.63 (-7.99, -3.27)*

Note: '*' denotes a 95% confidence interval does not contain 0. Models were adjusted for participant age, annual household income level, education level, measured body fat (%), log(mean daily steps), employment, being diabetic, self-reported health condition, and Godin activity level. Urban resident group was the reference group.



Appendix Figure 36 Sensitivity analysis of intervention (or intervention &weekdays vs. intervention &weekend) effect on HI[individual] in ITT and PP. The population mean of HI difference(°C) between HI[individual] and HI[WS] on baseline days (intervention index = 0), intervention &weekdays (intervention index =1), and intervention &weekends (intervention index =2) in different population groups by using Intent-to-treat (ITT) and Per-Protocol (PP) dataset. The 95% confidence intervals are shown.

Appendix Table 18 Sensitivity analysis of intervention (or intervention &weekdays vs. intervention &weekend) effect on HI[individual] in ITT and PP. Results of linear mixed models describing the relation between the intervention (weekdays vs. weekends) and the daily mean

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	28.96 (23.09, 34.81)	26.32 (17.22, 35.42)	35.3 (23.93, 46.66)	22.81 (7.34, 38.27)
HI[neighborhood] Mean (°C)	0.07 (-0.07, 0.22)	-0.04 (-0.26, 0.19)	-0.09 (-0.38, 0.21)	NA
HI[WS] Mean (°C)	NA	NA	NA	0.39 (-0.06, 0.83)
Wind speed Mean (m/s)	0.43 (-0.05, 0.91)	0.71 (-0.1, 1.52)	0.47 (-0.27, 1.21)	0.89 (-0.22, 2.01)
Age	0.02 (-0.02, 0.05)	0.01 (-0.04, 0.05)	0.04 (-0.01, 0.10)	0.03 (-0.08, 0.15)
Annual household income >20k	-0.75 (-1.67, 0.18)	-0.02 (-1.38, 1.35)	-0.96 (-2.86, 0.95)	-1.86 (-3.89, 0.18)
Education >high school	-0.36 (-1.24, 0.53)	-1.03 (-2.28, 0.23)	0.26 (-1.50, 2.02)	1.28 (-0.51, 3.08)
Body fat (%)	-0.06 (-0.13, 0.00)	0.05 (-0.06, 0.15)	-0.1 (-0.23, 0.03)	-0.13 (-0.25, -0.02)*
Log (daily steps)	-0.05 (-0.26, 0.16)	0.1 (-0.2, 0.39)	-0.41 (-0.77, -0.05)*	0.09 (-0.38, 0.56)
Employed	0.29 (-0.64, 1.21)	-0.41 (-1.72, 0.9)	1.01 (-0.63, 2.64)	NA
Diabetic	-0.17 (-1.21, 0.87)	0.1 (-1.23, 1.43)	-0.99 (-3.11, 1.13)	-2.6 (-6.13, 0.91)
Health condition in Fair[a]	-0.11 (-1.2, 0.99)	-0.89 (-2.41, 0.63)	1.22 (-0.71, 3.15)	-0.55 (-2.91, 1.81)

Health condition in Poor[a]	0.54 (-2.22, 3.3)	1.41 (-2.63, 5.46)	-2.03 (-7.44, 3.38)	-0.14 (-4.75, 4.47)
Godin inactivity	-0.03 (-0.89, 0.82)	0.00 (-1.27, 1.27)	0.38 (-1.18, 1.94)	-0.3 (-2.05, 1.45)
Intervention*weekday	-0.38 (-0.7, -0.07)*	-0.38 (-0.82, 0.06)	-0.21 (-0.74, 0.32)	-1.01 (-1.73, -0.29)*
Intervention*weekends	-0.98 (-1.36, -0.61)*	-0.64 (-1.12, -0.16)*	-0.66 (-1.49, 0.16)	-2.85 (-3.68, -2.01)*
WS Rain	0.09 (-0.24, 0.41)	0.23 (-0.18, 0.64)	-0.05 (-0.7, 0.61)	0.05 (-0.78, 0.87)

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily mean indicates that HI[neighborhood] or HI[WS] daily mean was not included in the model selection based on AIC. Models for all participants did not include a group factor.

Appendix Table 19 Sensitivity analysis of intervention (or intervention &weekdays vs. intervention &weekend) effect on HI[individual] in ITT and PP. Results of linear mixed models describing the relation between the intervention (weekdays vs. weekends) and the daily max

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	49.22 (37.34, 61.04)	36.39 (19.93, 52.86)	55.35 (33.26, 77.29)	10.81 (-39.98, 61.64)
HI[neighborhood] Max (°C)	0.04 (-0.18, 0.27)	0.04 (-0.26, 0.33)	0.00 (-0.45, 0.45)	NA
HI[WS] Max (°C)	NA	NA	NA	1.44 (0.10, 2.79)*
Wind speed Max (m/s)	0.49 (0.21, 0.76)*	0.25 (-0.11, 0.60)	1.01 (0.53, 1.5)*	0.36 (-0.51, 1.23)
Age	-0.01 (-0.07, 0.05)	-0.01 (-0.08, 0.07)	0.04 (-0.05, 0.13)	0.08 (-0.16, 0.32)
Annual household income >20k	-0.74 (-2.34, 0.86)	0.86 (-1.22, 2.93)	-4.02 (-7.03, -1.01)*	-2.71 (-7.00, 1.6)
Education >high school	-0.72 (-2.24, 0.80)	-0.84 (-2.74, 1.08)	-0.76 (-3.58, 2.06)	0.83 (-2.96, 4.68)
Body fat (%)	-0.21 (-0.33, -0.10)*	0.00 (-0.16, 0.16)	-0.18 (-0.39, 0.02)	-0.29 (-0.53, -0.06)*
Log (daily steps)	-0.37 (-1.00, 0.26)	-0.03 (-0.81, 0.76)	-1.37 (-2.46, -0.28)*	-0.55 (-2.24, 1.14)
Employed	1.73 (0.12, 3.34)*	-0.78 (-2.76, 1.22)	3.55 (1.00, 6.11)*	NA
Diabetic	-0.71 (-2.5, 1.09)	-0.17 (-2.19, 1.86)	-1.62 (-4.90, 1.67)	-4.47 (-11.94, 2.87)
Health condition in Fair[a]	0.43 (-1.46, 2.32)	-0.66 (-2.97, 1.66)	1.13 (-1.86, 4.11)	-1 (-5.97, 4.01)

Health condition in Poor[a]	0.65 (-4.07, 5.37)	-0.55 (-6.68, 5.58)	-11.15 (-19.52, -2.77)*	7.42 (-2.04, 16.9)
Godin inactivity	-0.49 (-1.96, 0.98)	-0.67 (-2.6, 1.26)	-0.83 (-3.32, 1.65)	0.16 (-3.52, 3.81)
Intervention*weekday	-0.74 (-1.71, 0.23)	-0.01 (-1.25, 1.23)	-0.77 (-2.50, 0.97)	-4.43 (-7.26, -1.61)*
Intervention*weekends	-2.22 (-3.24, -1.2)*	-0.49 (-1.75, 0.78)	-0.68 (-2.63, 1.28)	-8.77 (-11.6, -5.94)*
WS Rain	-0.09 (-1.02, 0.84)	0.92 (-0.09, 1.93)	-2.32 (-4.32, -0.34)*	-1.89 (-5.2, 1.42)

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily max indicates that HI[neighborhood] or HI[WS] daily max was not included in the model selection based on AIC. Models for all participants did not include a group factor.

Appendix Table 20 Sensitivity analysis of intervention (or intervention &weekdays vs. intervention &weekend) effect on HI[individual] in ITT and PP. Full results of linear mixed models describing the relation between the intervention and the daily mean heat index experienced by individuals during the intervention in different population groups in PP.

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	24.28 (18.82, 29.74)	27.62 (18.61, 36.65)	30.25 (20.21, 40.27)	3.64 (-10.05, 17.31)
HI[WS] Mean (°C)	NA	NA	NA	0.94 (0.58, 1.31)*
HI[neighborhood] Mean (°C)	0.20 (0.07, 0.33)*	-0.09 (-0.32, 0.13)	0.05 (-0.18, 0.28)	NA
Wind speed Mean (m/s)	0.73 (0.23, 1.23)*	0.98 (0.19, 1.77)*	0.57 (-0.21, 1.36)	1.76 (0.59, 2.95)*
Age	0.01 (-0.02, 0.05)	0.00 (-0.05, 0.05)	0.04 (-0.01, 0.10)	0.04 (-0.08, 0.15)
Annual household income >20k	-0.8 (-1.74, 0.14)	-0.20 (-1.60, 1.21)	-1.04 (-2.95, 0.87)	-1.77 (-3.8, 0.26)
Education >high school	-0.37 (-1.27, 0.53)	-0.97 (-2.26, 0.32)	0.17 (-1.59, 1.93)	1.06 (-0.73, 2.85)
Body fat (%)	-0.06 (-0.13, 0.01)	0.05 (-0.05, 0.15)	-0.08 (-0.22, 0.05)	-0.12 (-0.23, -0.005)*
Log (daily steps)	-0.03 (-0.26, 0.2)	0.1 (-0.23, 0.42)	-0.37 (-0.76, 0.03)	0.28 (-0.23, 0.79)
Employed	0.27 (-0.67, 1.21)	-0.44 (-1.79, 0.91)	0.91 (-0.73, 2.55)	NA
Diabetic	-0.16 (-1.22, 0.9)	0.1 (-1.27, 1.47)	-1.03 (-3.15, 1.08)	-2.54 (-6.07, 0.96)
Health condition in Fair[a]	-0.02 (-1.14, 1.11)	-0.87 (-2.44, 0.71)	1.31 (-0.63, 3.24)	-0.61 (-2.99, 1.76)

Health condition in Poor[a]	0.71 (-2.1, 3.51)	1.89 (-2.31, 6.07)	-2.20 (-7.59, 3.18)	0.03 (-4.56, 4.62)
Godin inactivity	-0.04 (-0.91, 0.82)	0.00 (-1.31, 1.30)	0.38 (-1.19, 1.93)	-0.51 (-2.26, 1.26)
Intervention	-0.49 (-0.79, -0.20)*	-0.30 (-0.71, 0.11)	-0.18 (-0.73, 0.37)	-1.67 (-2.32, -1.01)*
WS Rain	0.27 (-0.07, 0.62)	0.35 (-0.06, 0.76)	0.07 (-0.63, 0.76)	0.15 (-0.74, 1.03)

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily mean indicates that HI[neighborhood] or HI[WS] daily mean was not included in the model selection based on AIC. Models for all participants did not include a group factor.

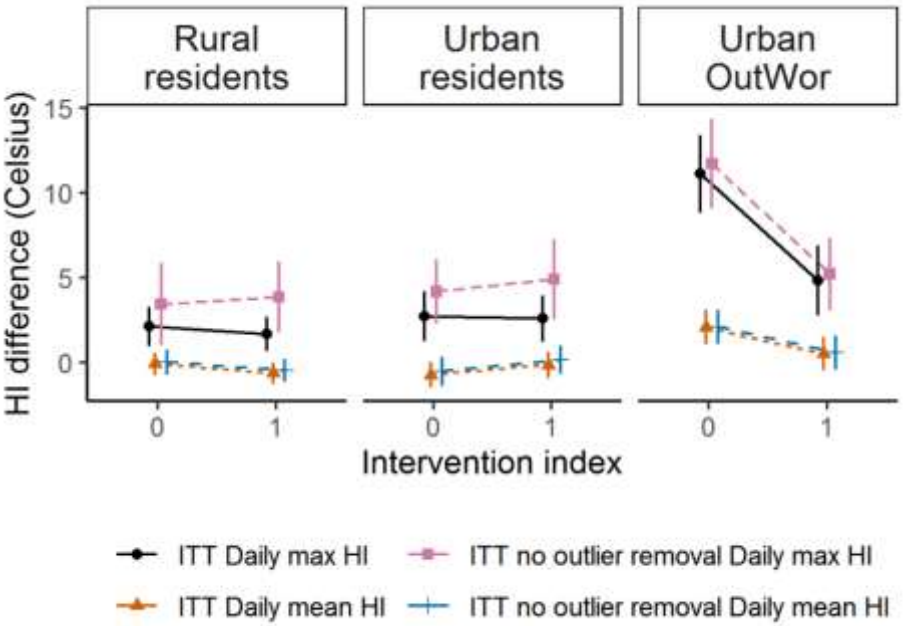
Appendix Table 21 Sensitivity analysis of intervention (or intervention &weekdays vs. intervention &weekend) effect on HI[individual] in ITT and PP. Full results of linear mixed models describing the relation between the intervention and the daily max heat index experienced by individuals during the intervention in different population groups in PP.

Group	All	Rural residents	Urban residents	Urban OutWor
Fixed effect	β 95%CI	β 95%CI	β 95%CI	β 95%CI
Intercept	45.65 (3.41, 57.78)	34.68 (17.3, 52.04)	53.82 (31.84, 75.62)	-3.54 (-52.6, 45.53)
HI[WS] Max (°C)	NA	NA	NA	1.82 (0.53, 3.13)*
HI[neighborhood] Max (°C)	0.07 (-0.16, 0.3)	0.05 (-0.26, 0.36)	-0.09 (-0.53, 0.35)	NA
Wind speed Max (m/s)	0.55 (0.26, 0.84)*	0.37 (-0.02, 0.75)	1.00 (0.48, 1.51)*	0.58 (-0.33, 1.48)
Age	-0.01 (-0.07, 0.05)	-0.02 (-0.09, 0.06)	0.03 (-0.06, 0.11)	0.09 (-0.15, 0.33)
Annual household income >20k	-0.62 (-2.26, 1.01)	0.75 (-1.44, 2.91)	-4.1 (-6.99, -1.19)*	-2.31 (-6.57, 1.95)
Education >high school	-0.85 (-2.40, 0.71)	-0.81 (-2.82, 1.22)	-0.76 (-3.45, 1.91)	0.53 (-3.21, 4.29)
Body fat (%)	-0.18 (-0.30, -0.07)*	0.01 (-0.15, 0.18)	-0.11 (-0.31, 0.09)	-0.29 (-0.53, -0.05)*
Log (daily steps)	-0.22 (-0.91, 0.47)	0.03 (-0.86, 0.92)	-1.06 (-2.2, 0.09)	-0.48 (-2.22, 1.26)
Employed	1.45 (-0.19, 3.10)	-0.99 (-3.07, 1.10)	2.73 (0.27, 5.2)*	NA
Diabetic	-0.94 (-2.79, 0.90)	-0.34 (-2.46, 1.81)	-2.01 (-5.13, 1.13)	-4.23 (-11.61, 3.00)
Health condition in Fair[a]	0.84 (-1.12, 2.81)	-0.51 (-2.98, 1.99)	1.66 (-1.2, 4.53)	0.01 (-5.09, 5.07)

Health condition in Poor[a]	0.93 (-3.92, 5.78)	0.57 (-6.06, 7.17)	-10.92 (-18.78, -3.03)*	7.94 (-1.30, 17.20)
Godin inactivity	-0.58 (-2.08, 0.91)	-0.69 (-2.72, 1.35)	-0.39 (-2.77, 1.97)	-0.52 (-4.22, 3.12)
Intervention	-0.99 (-1.90, -0.08)*	0.35 (-0.85, 1.55)	-0.22 (-1.89, 1.45)	-6.48 (-8.95, -4.01)*
WS Rain	-0.04 (-1.05, 0.96)	1.16 (0.08, 2.25)*	-2.61 (-4.63, -0.61)*	-3.19 (-6.38, 0.01)

Appendix Table 1

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[neighborhood] or HI[WS] daily max indicates that HI[neighborhood] or HI[WS] daily max was not included in the model selection based on AIC. Models for all participants did not include a group factor.



Appendix Figure 37 The effect of ITT outlier removal on daily mean and max HI difference(°C) between HI[individual] and HI[WS]. The population mean or max of the daily mean HI difference(°C) between HI[individual] and HI[WS] on baseline days (intervention index = 0) and intervention days (intervention index =1) in different population groups in ITT and ITT-no outlier removal datasets. The 95% confidence intervals are shown.

Appendix Table 22 Full results of linear mixed models describing the relation between the intervention and the daily mean or max heat index experienced by individuals during the intervention across all participants in ITT-no outlier removal dataset.

Models	Model 1	Models	Model 2
Dependent variable	Daily mean HI[individual]	Dependent variable	Daily max HI[individual]
Fixed effect	β 95%CI	Fixed effect	β 95%CI
Intercept	24.29 (18.63, 29.95)	Intercept	52.72 (34.91, 70.38)
HI[WS] Mean (°C)	NA	HI[WS] Max (°C)	NA
HI[neighborhood] Mean (°C)	0.22 (0.08, 0.35)*	HI[neighborhood] Max (°C)	0.06 (-0.27, 0.40)
Wind speed Mean (m/s)	0.68 (0.17, 1.19)*	Wind speed Max (m/s)	0.30 (-0.12, 0.72)
Age	0.02 (-0.02, 0.05)	Age	0.01 (-0.08, 0.09)
Annual household income >20k	-0.81 (-1.76, 0.15)	Annual household income >20k	-1.7 (-4.07, 0.67)
Education >high school	-0.52 (-1.43, 0.39)	Education >high school	-1.56 (-3.79, 0.69)
Body fat (%)	-0.07 (-0.14, -0.001)*	Body fat (%)	-0.25 (-0.42, -0.08)*
Log (daily steps)	-0.03 (-0.26, 0.21)	Log (daily steps)	-0.58 (-1.55, 0.40)
Employed	0.47 (-0.49, 1.43)	Employed	3.19 (0.81, 5.57)*
Diabetic	-0.15 (-1.23, 0.93)	Diabetic	-0.43 (-3.09, 2.23)
Health condition in Faira	-0.58 (-1.72, 0.56)	Health condition in Faira	-0.81 (-3.61, 2.00)
Health condition in Poora	0.30 (-2.55, 3.14)	Health condition in Poora	-1.08 (-8.04, 5.88)
Godin inactivity	0.09 (-0.79, 0.97)	Godin inactivity	0.35 (-1.81, 2.52)
Intervention	-0.51 (-0.83, -0.19)*	Intervention	-0.58 (-1.93, 0.76)
WS Rain	0.22 (-0.13, 0.57)	WS Rain	-0.15 (-1.60, 1.29)

Note: '*' indicates a 95% confidence interval does not contain 0. NA in HI[WS] daily mean indicates that HI[WS] daily mean was not included in the model selection based on AIC. Models for all participants did not include a group factor.

Appendix Table 23 Body measurement change ratios (%) of participants (N=177) including extreme body measurement change ratios.

Body measurement change ratio(%)[a]	Mean (95%CI)	Participant N	Obese level[b]	β 95%CI	Participant N
Body fat	-0.22 (-1.22, 0.79)	172	Normal	-0.92 (-3.56, 1.71)	9
			Overweight	-0.51 (-2.20, 1.18)	29
			Obese	-0.1 (-1.34, 1.13)	134
Body water	0.40 (-0.25, 1.05)	172	Normal	0.47 (-1.20, 2.15)	9
			Overweight	0.24 (-0.88, 1.35)	29
			Obese	0.43 (-0.36, 1.22)	134
Muscle mass	-1.32 (-1.99, -0.66)*	172	Normal	-0.42 (-2.39, 1.55)	9
			Overweight	-1.21 (-2.48, 0.07)	29
			Obese	-1.41 (-2.2, -0.61)*	134

Note: '*' denotes a 95% confidence interval does not contain 0.

[a] $Body\ measurement\ change\ ratio = \frac{body\ measurement_{after} - body\ measurement_{before}}{body\ measurement_{before}} \times 100\%$

[b]Obese level: Normal = BMI <25, Overweight = BMI <30 and ≥25, Obese = BMI ≥30.

Appendix D Supplemental Materials to Manuscript 4

Appendix Table 24 Characteristics of participants in Alabama, 2020.

	Both	Wilcox County (rural)	Birmingham city (urban)	P-value
Number	101	52	49	
Age				0.72[a]
Mean(95%CI)	52.0(49.3-54.8)	51.5 (47.6 to 55.5)	52.6(48.6 to 56.5)	
Median(range)	56(19-72)	55.5(21-70)	56(19-72)	
Age groups				0.99
≤40 years old	17(17%)	9(17%)	8(16%)	
41-50 years old	23(23%)	11(21%)	12(24%)	
51-64 years old	47(47%)	25(48%)	22(45%)	
≥65 years old	14(14%)	7(13%)	7(14%)	
Sex				0.10
Male	16(16%)	5(10%)	11(22%)	
Female	85(84%)	47(90%)	38(78%)	
How long have you lived in this community?				2.0E-03*
0-5 years	26(26%)	8(15%)	18(37%)	
6-15 years	24(24%)	9(17%)	15(31%)	
More than 15 years	51(50%)	35(67%)	16(33%)	
Ethnicity or ancestry				NA
Black or African	101(100%)	52(100%)	49(100%)	
Highest level of education				0.24
≤ High school	39(39%)	19(37%)	20(41%)	
Post-secondary or some college courses	45(45%)	21(40%)	24(49%)	
≥ Bachelor's degree	17(17%)	12(23%)	5(10%)	
Annual household incomes				0.39
Less than $20,000	58(57%)	33(63%)	25(51%)	
$20,000 to $49,999	31(31%)	15(29%)	16(33%)	
$50,000 to $74,999	8(8%)	2(4%)	6(12%)	
$75,000 to more	4(4%)	2(4%)	2(4%)	
General health condition				0.89
Excellent	21(21%)	12(23%)	9(18%)	
Good	59(58%)	29(56%)	30(61%)	
Fair	21(21%)	11(21%)	10(20%)	
Poor	0(0%)	0(0%)	0(0%)	
Did you participate in a study in the summer of 2017 by wearing a temperature monitor on your shoe?				6.1E-06*
Yes	42(42%)	33(63%)	9(18%)	
No	59(58%)	19(37%)	40(82%)	
Have you participated in focus groups or table discussions about environmental priorities with us in the past 5 years?				3.2E-07*
Yes	45(45%)	36(69%)	9(18%)	

No	56(55%)	16(31%)	40(82%)

Note: p-values were obtained from Fisher's exact tests. [a]p-value 0.72 was obtained from student's t-test. "*" denotes a statistically significant difference with p-values <0.05. CI = confidence interval.

Appendix Table 25 Comparison of self-reported participant sociodemographic versus population sampled from (based on U.S. Census data).

Location	Birmingham city		Wilcox County	
Data source	U.S. Census	Study participants	U.S. Census	Study participants
Person 65 years and over, percent	14.9%	16.3%	20.3%	19.2%
Female persons, percent	52.8%	78%	52.5%	90%
Black or African American	69.9%	100%	71.1%	100%
High school graduate or higher, percent of persons aged 25 years+	86.7%	97.8%	76.5%	89.1%
Bachelor's degree or higher, percent of persons aged 25 years+	27.4%	11.1%	12.5%	17.4%
Median household income	$37,375	51% Less than $20,000	$31,014	63% Less than $20,000

Appendix Table 26 Perception of health and safety change due to recent police brutality in different age groups.

Factors	Location	Participants number (%)	Age group	Participants number who answered "yes"	Total participant number in age group	Participants (%) in each age group	P-value from Fisher's exact test
Change perception of safety for visiting public spaces or recreational areas	Both	43(43%)	Below 40	5	17	29%	0.42
			41 to 50	9	23	39%	
			51 to 64	24	47	51%	
			Above 65	5	14	36%	
	Rural	25(48%)	Below 40	2	9	22%	0.37
			41 to 50	5	11	45%	
			51 to 64	14	25	56%	
			Above 65	4	7	57%	
	Urban	18(37%)	Below 40	3	8	38%	0.56
			41 to 50	4	12	33%	
			51 to 64	10	22	45%	
			Above 65	1	7	14%	
Change trust in local emergency manageme nt or health care providers	Both	39(39%)	Below 40	6	17	35%	0.76
			41 to 50	7	23	30%	
			51 to 64	20	47	43%	
			Above 65	6	14	43%	
	Rural	17(33%)	Below 40	2	9	22%	0.35
			41 to 50	2	11	18%	
			51 to 64	9	25	36%	
			Above 65	4	7	57%	
	Urban	22(45%)	Below 40	4	8	50%	0.81
			41 to 50	5	12	42%	
			51 to 64	11	22	50%	
			Above 65	2	7	29%	
Affect your health, or health of your family and friends	Both	2(2%)	Below 40	0	17	0%	1
			41 to 50	0	23	0%	
			51 to 64	2	47	4%	
			Above 65	0	14	0%	
	Rural	1(2%)	Below 40	0	9	0%	1
			41 to 50	0	11	0%	
			51 to 64	1	25	4%	
			Above 65	0	7	0%	
	Urban	1(2%)	Below 40	0	8	0%	1
			41 to 50	0	12	0%	
			51 to 64	1	22	5%	
			Above 65	0	7	0%	

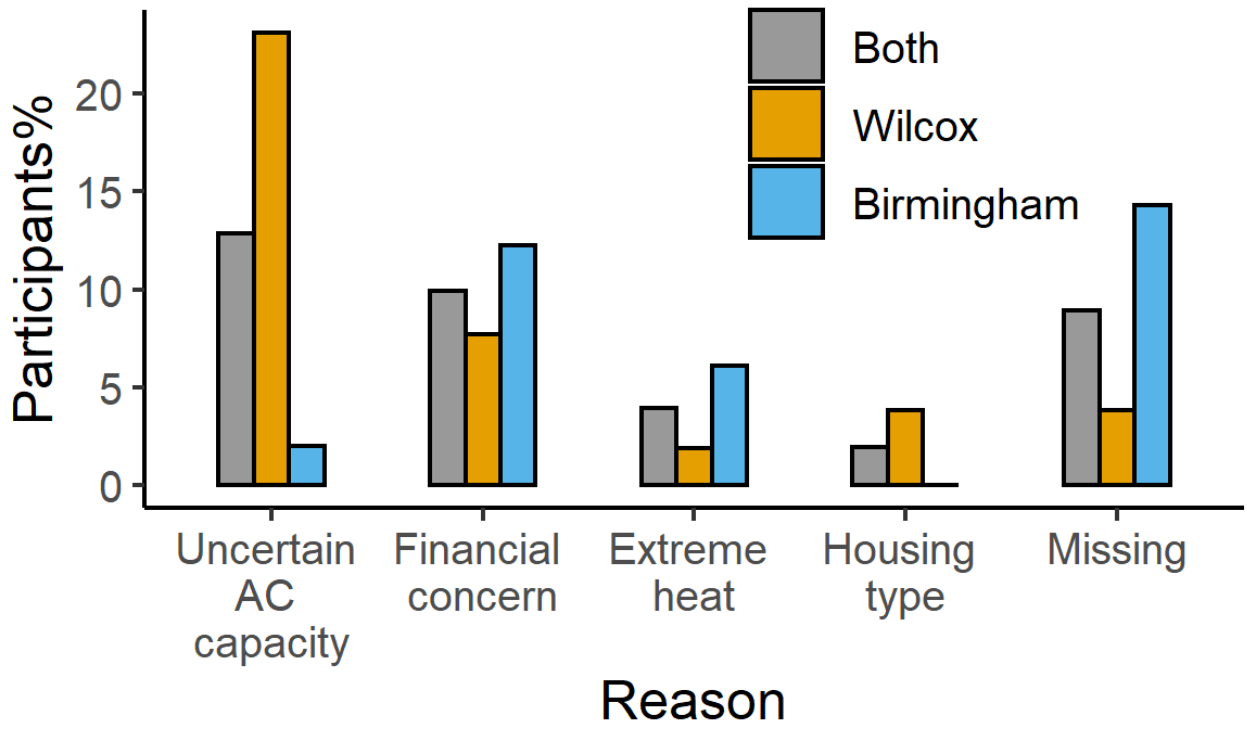
Appendix Table 27 Perception of health and safety change due to recent police brutality among participants with consideration of how long they have lived in the community.

Factors	Location	Participants number (%) who answered "yes"	Residence duration in this community	Participants number who answered "yes"	Total participant number in each residence duration group	Participants (%) who answered "yes" in each residence duration group	P-value from Fisher's exact test
Change perception of safety for visiting public spaces or recreational areas	Both	43(43%)	0-5 years	5	26	19%	0.002
			6-15 years	13	24	54%	
			> 15 years	25	51	49%	
	Rural	25(48%)	0-5 years	1	8	13%	0.08
			6-15 years	4	9	44%	
			> 15 years	20	35	57%	
	Urban	18(37%)	0-5 years	4	18	22%	0.08
			6-15 years	9	15	60%	
			> 15 years	5	16	31%	
Change trust in local emergency manageme nt or health care providers	Both	39(39%)	0-5 years	7	26	27%	0.24
			6-15 years	12	24	50%	
			> 15 years	20	51	39%	
	Rural	17(33%)	0-5 years	0	8	0%	0.08
			6-15 years	4	9	44%	
			> 15 years	13	35	37%	
	Urban	22(45%)	0-5 years	7	18	39%	0.72
			6-15 years	8	15	53%	
			> 15 years	7	16	44%	
Affect your health, or health of your family and friends	Both	2(2%)	0-5 years	1	26	4%	1
			6-15 years	0	24	0%	
			> 15 years	1	51	2%	
	Rural	1(2%)	0-5 years	0	8	0%	1
			6-15 years	0	9	0%	
			> 15 years	1	35	3%	
	Urban	1(2%)	0-5 years	1	18	6%	1
			6-15 years	0	15	0%	
			> 15 years	0	16	0%	

Appendix Table 28 Follow-up survey results.

Factors	Participants number (%) in Both	Participants number (%) in Rural	Participants number (%) in Urban	P-value[a]
Feel you have been able to stay cool so far in Summer 2020	96(95%)	48(92%)	48(98%)	0.62
Have concerns that you will not be able to stay cool in this upcoming hot weather that is forecasted	38(38%)	21(40%)	17(35%)	0.54
Will use methods to keep you and your friends and family cool during the upcoming heatwave	70(69%)	36(69%)	34(69%)	1

Note: [a]p-values were obtained between response in the urban location vs. the rural location concurrently in Fisher's exact tests.



Appendix Figure 38 Reasons reported by participants who reported having concerns (N=21 (40%) rural participants, N=17 (35%) urban participants) that they would not be able to stay cool in the upcoming hot weather forecasted in 2020.