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Older pedestrians' physiological reactions are indicative of stressful and non-stressful urban built environment conditions

Alex Torku, PhD[1], Albert P. C. Chan, PhD[2], Esther H. K. Yung, PhD[3], JoonOh Seo, PhD[4]

[1]Lecturer, Department of Civil Engineering, Surveying and Construction Management, Kingston University London, Penrhyn Road, Kingston upon Thames, Surrey, KT1 2EE, United Kingdom (corresponding author).
Email: a.torku@kingston.ac.uk

[2]Chair Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University, 11 Yuk Choi Rd, Hung Hom, Kowloon, Hong Kong.

[3]Associate Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University, 11 Yuk Choi Rd, Hung Hom, Kowloon, Hong Kong.

[4]Associate Professor, Department of Building and Real Estate, The Hong Kong Polytechnic University, 11 Yuk Choi Rd, Hung Hom, Kowloon, Hong Kong.

Abstract

This research examines whether the physiological responses (measured using wearable sensors) among older adults vary by stress and non-stress environmental conditions. The physiological responses (specifically, heart rate variability and electrodermal activity) and perceived stress among ten older adults were measured while walking along an urban path. The path condition was assessed by two trained observers. The differences in participants' physiological responses (individual and collective) and individual differences (including body mass index and gender) under perceived stressful and non-stressful path conditions were tested using Wilcoxon signed-rank. A test for clustering of physiological responses was conducted among all participants and associated perceived stress and non-stress path conditions. In addition, a spatio-temporal analysis was conducted to detect variation in physiological responses within the stress and non-stress path conditions. Results indicated that, on average, participants experienced a statistically significant higher physiological response to environmental conditions perceived as non-stress than environmental conditions perceived as stress. Women experienced a significantly higher physiological response to non-stress environmental conditions than men. Stressful environmental condition poses high demand to older adults with a body mass index above 24.9. Although personal factors and time-dependent environmental factors influence the effectiveness of wearable physiological sensing, wearable physiological sensing can complement existing built environment assessment approaches to improve active ageing and age-friendly city and community design.

Keywords

Older adult, Environmental stress, Wearable physiological sensing

THIS STUDY EXAMINES WHETHER OLDER PEDESTRIANS' PHYSIOLOGICAL REACTIONS (MEASURED USING WEARABLE SENSORS) ARE INDICATIVE OF URBAN BUILT ENVIRONMENT STRESSORS.

Introduction

Globally, one in six people is expected to age 65 years or older by 2050[1]. With the changing age structure of the projected population, many cities and communities are now committed to promoting active ageing. The World Health Organisation (WHO) propounded the active ageing concept to stimulate cities and communities to create an enabling environment for older adults to continue participating in social, economic, civic engagement and physical activity in order to enhance their quality of life as they age[2-3]. However, attaining this active ageing potential requires older adults to achieve successful mobility to gain access to their desired places (physical environment) and people (social environment). Despite the fundamental importance of mobility to active ageing, studies have reported a decline in the older adults' mobility indices such as time spent outdoors, trip frequency and trip distance[4-5]. To promote mobility, it is not enough to target only the individual (e.g., physical activity counselling and educational interventions to increase older adults' physical activity) because environmental barriers also limit mobility among older adults[6].

An environmental barrier is a relative concept; dependent on the interaction between an individual's capability and environmental demand. When environmental demand meets a person's capability, the person can achieve successful mobility. On the other hand, the person experience stress and/or their mobility is limited when the environmental demand exceeds their capability[7-9]. Stress is a type of relationship between a person and the environment which occurs when demands tax or exceed the person's capability[10]. As functional capacity declines with ageing, it is more likely for older adults to experience stress—potentially leading to mobility limitation—in the built environment than the average person. Older adults' interaction with excessive environmental demands can even be overwhelming in cities and communities with built environment infrastructure approaching their design life.

Recent advancements in sensing technologies offer a great opportunity to continuously monitor and provide a more human-centred assessment of the built environment[11-12]. Human-centric sensing is a new generation of interdisciplinary research that measures human users' direct reactions to their interactions with different built environments[13]. Older adults usually achieve mobility in outdoor neighbourhood environments either by walking on foot or with mobility aids. The common mobility aids include a walking stick, walking frame and wheelchair. Most of the existing studies that use wearable sensing technologies focus only on humans or the interaction between humans. A few of these studies that focus on human-environment interaction often attach the sensors to the mobility aid to assess the environmental condition[14-15]. An example is a recent study that attached inertial sensors to the users' wheelchairs to detect urban features like curb ramps, steps or other obstacles along a path[14]. Although these works prove the feasibility of using sensor data collected during human movement to assess an environmental condition, they might not be a good representation of human-environment interaction. Human responses to environmental conditions are more complicated than mobility aid usage. As a result, sensors attached to older adults are inherently subject to greater variability (than sensors attached to mobility aids), which could affect built environment assessment. Therefore, it is essential to understand the variability in older adults' responses to different environmental conditions before adopting human-centric sensing.

Research aim

This study examines whether older pedestrians' physiological reactions (collected from wearable sensors) are indicative of urban built environment stressors. The physiological signals are involuntary actions or responses that are almost impossible to notice by external observation because they relate to how a living organism or bodily part functions[16]. When the body is stressed, the autonomic nervous system provokes human responses, which are reflected in their physiological signals[16-17]. This research examines whether the physiological responses that older adults naturally and unconsciously portray while interacting with different environmental conditions may offer vital information about the environment's condition. The results from this study will be useful for urban planners and future researchers who want to adopt human-centric sensing to achieve a more efficient and timely assessment of older adults-environment interactions to inform urban planning and design. Figure 1 is an overview of the study.

Experiment design and methods

Experiment design

A 570 m walking path was predetermined in the neighbourhood of Hung Hom, Hong Kong, as shown in Figure 2. The path consists of spacious and narrow streets, green and high-density building areas, playgrounds, a gas station, a car wash, a car fitting shop, crosswalks (with and without traffic or pedestrian signals), sidewalks with even and uneven slopes, different street materials, among other features. Ten older adults (7 women, 3 men, age range = 65-75, average age = 68, body mass index above 24.9 = 6, body mass index below 24.9 = 4) were recruited to participate in an environmental walk. Eligibility was assessed based on the participant's ability to walk unassisted by another person for at least 15 min and to meet the recommended score for the Cantonese version of the Mini-Mental State Examination[18-19]. The environmental walk was carried out in November 2019 between 10 am and 4 pm. The environment temperature ranges from 24°C-29°C and the humidity ranges from 41%-55%.

The environmental walk was divided into two phases. During the first phase, the participants were equipped with non-invasive wearable sensors while they walked the path from start to finish (as shown in Figure 2) at a self-directed pace. Two commercial off-the-shelf wearable sensors, a wristband-type sensor (Empatica E4) and a belt-clip-type GPS sensor (Qstarz BT-Q1000XT), were used for data collection. The wristband recorded electrodermal activity (EDA) (at 4 Hz) and computed instantaneous heart rate (IHR) (at 1 Hz) from the inter-beat interval (obtained from photoplethysmography signal). The physiological responses were spatially referenced using the GPS coordinates (latitude and longitude) (recorded at 1 Hz). Older adults' IHR and EDA were collected during a 10 min rest period (for baseline measurement) and the entire period of the first phase of the environmental walk. During the second phase, the participants walked the path without wearing the sensors. Instead, each participant was asked to categorise the path into "non-stress" and "stress" based on their perceived interaction and experience with the path. The participants also stated the intensity of their perceived stress (low or high intensity).

Prior to the environmental walk, two trained observers assessed the path using the Environment in Asia Scan Tool–Hong Kong version to facilitate comparisons with older adults' physiological and perceived responses[20]. The experiment protocol was approved by the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic University (Reference Number: HSEARS20190826002).

Data pre-processing

Artefacts in the IHR data were corrected and heart rate variability (HRV) was calculated using a proprietary algorithm[21]. The raw EDA data was low pass filtered using a Butterworth filter with a cut-off frequency of 0.28 Hz and smoothed with a moving average filter to remove non-EDA related sensor readings[22]. Each participant's IHR and EDA data were baseline normalised to reduce inter-individual variance.

Physiological reflectors of human-environmental stressful interactions

The path for the environmental walk was categorised into environmental conditions perceived as non-stress and stress by the older adults. Older adults' physiological responses to these environmental conditions were analysed by assessing their autonomic nervous system (ANS). The ANS is one of the major neural pathways activated by stress[23]. HRV and EDA are reliable indicators of the sympathetic and parasympathetic nervous systems[23-24]. The parasympathetic nervous system modulates heart rate (HR) at all frequencies between 0.15-0.4 Hz. The sympathetic nervous system modulates HR at frequencies between 0.04-0.15 Hz[24]. To precisely model the effect of environmental stressors, the spectral power of the low frequency (LF) band (0.04-0.15) and high frequency (HF) band (0.15-0.4) were calculated. The ratio LF/HF was derived to represent the ratio of the sympathetic to parasympathetic influence on the heart.

An increase in the eccrine sweat gland activity is observed when the sympathetic nervous system is stimulated, thus changing the conductivity of the skin[22]. EDA measures the conductivity of the skin and is one of the most frequently employed signals for detecting stress[22-23]. To precisely model the effect of environmental stressors, the EDA was decomposed into two components—phasic component and tonic component—using a continuous decomposition analysis[25]. The phasic component results from an underlying sympathetic reaction to a stimulus, while the tonic component results from a tonic stimulus and changes slowly over time[22,25]. Because the tonic EDA component cannot be linked to a specific stimulus, the authors used only the phasic EDA component to represent older adults' physiological responses.

The expected physiological effect of a stressor occurs slightly after the stimulus. The onset of a skin conductance response, when caused by a stimulus, is typically between 1 and 5 sec after the delivery of the stimulus[23]. To fully capture the physiological effect of a stressful environmental condition, the authors computed the maximum value of phasic activity within 10 sec response windows (PhasicMax) extracted from the phasic EDA component as an indicator of older adults' physiological response. The LF/HF was derived from a window size of 60 sec using Welch's periodograms[21]. Based on previous studies, a short-term window of 60 sec can produce informative HRV measures[26]. Using the respective window size and advanced by 1 sec for each second of the walk (to correspond to the 1 Hz GPS data), continuous calculations of LF/HF and PhasicMax were made for the entire duration of each participant's walk on the path.

Statistical and spatial analysis

A Wilcoxon signed-rank test was conducted to understand whether the physiological responses to environmental conditions perceived as non-stress was statistically and significantly different from environmental conditions perceived as stress. Spatial clustering analysis was conducted using Getis-Ord General G to confirm any spatial association in participants' physiological responses. To determine locations on the path that stimulated a common physiological response among multiple participants, the authors conducted a hotspot analysis using Getis-Ord Gi* statistics.

Spatiotemporal analysis

All participants' physiological responses were scaled and aggregated into a space-time cube (STC), as depicted in Figure 3. Each bin in the STC contains participants' physiological responses at a specific location (x,y) and time (t). A hexagon grid (here, set as 3 m along the path) was used to construct the bins because the circularity of the hexagon makes it more representative of the curves in the path. The participants' physiological responses were temporally binned at a daily interval for a total of ten days (only ten days of data were collected). Because each bin could span across more than one GPS point and contain multiple physiological responses, the median physiological response was computed to measure the central tendency of the multiple physiological responses in each bin. The emerging hotspot analysis tool in ArcGIS was used to identify the trends in the STC[27]. The temporal and spatial trends in the STC are analysed based on the Mann-Kendall trend test and Getis-Ord Gi*, respectively.

Results

Older adults' perceived assessment and observers' assessment of path condition

The path was labelled using the commonly perceived stress reported by the participants (Figure 4a). The observers rated each path segment as poor, moderate or good for each built environment domain: functionality, safety, and aesthetics (Figure 4b).

Older adults' physiological-environmental interaction

Statistical analysis: The results of the Wilcoxon signed-rank test (Table 1) indicate a statistically significant difference in some of the older adults' physiological responses to environmental conditions perceived as stress and non-stress. However, there are variations among some of the participant's physiological responses (LF/HF and PhasicMax). For instance, participant 3 experienced a statistically significantly higher LF/HF response whereas participant 6 experienced a statistically significantly lower LF/HF response to environmental conditions perceived as stress than environmental conditions perceived as non-stress. This variation was also observed in the PhasicMax responses of participants 1 and 2.

The differences in individual participant's physiological responses to the environmental conditions indicate that no specific physiological response represents an environment's condition; a high or low (LF/HF and PhasicMax) response can indicate either stress and/or non-stress environmental condition. Further analyses show that the differences in individual participant's physiological responses were due to their physical characteristics and gender. Physical characteristics were measured using the participant's body mass index [$weight/(height^2)$]. Body mass index (BMI) is a surrogate measure of body fatness and an approximate indicator of health, physical fitness, and activity level[28-29]. Studies have indicated an inverse relationship between physical activity and body mass index[30-31]. According to the Centres for Disease Control and Prevention, an adult with BMI below 18.5 is underweight, BMI between 18.5 and 24.9 is a healthy weight, BMI between 25.0 and 29.9 is overweight, and a BMI of 30.0 and above is obese[32]. In a non-stress environmental condition, only the data source from the heart rate (LF/HF) was statistically significant. Participants with a normal or healthy weight (BMI below 24.9) experienced higher LF/HF than overweight participants (BMI above 24.9). Only the data source from the SCR (PhasicMax) was statistically significant in stressful environmental conditions. Overweight participants (BMI above 24.9) experienced higher PhasicMax than participants with a normal or healthy weight (BMI below 24.9). This result could indicate that a stressful environmental condition poses high demand to overweight older adults. The female participants experienced a statistically significantly higher physiological response (both LF/HF and PhasicMax) to non-stress environmental conditions than the male participants.

The time to complete the environmental walk varies among the participants. This indicates that the differences in pace, walking behaviour and level of observation influenced how the participants interacted with the path hence their physiological responses. The source of the physiological response (i.e., the related organ) influenced some of the participants' physiological responses. For example, when the data is sourced from the heart rate (LF/HF) participant 5 experienced a statistically significantly higher physiological response to environmental conditions perceived as stress than environmental conditions perceived as non-stress. Whereas, when the data is sourced from the SCR (PhasicMax), the same participant (participant 5) experienced a statistically significantly lower physiological response to environmental conditions perceived as stress than environment conditions perceived as non-stress.

Aggregating all participants' physiological responses (collective sensing) produced a consistent result for the HR and SCR data sources. The result from the collective physiological responses shows that, on average, participants experienced a statistically significant higher physiological response to environmental conditions perceived as non-stress than conditions perceived as stress. A recent study (conducted by Chrisinger and King) on relatively younger adults reported similar physiological responses from EDA data (skin conductive)[33]. Chrisinger and King reported that EDA was higher in environmental conditions with favourable features and lower in environmental conditions with less favourable features[33].

Spatial analysis: The collective physiological responses were georeferenced to the corresponding GPS positions (Latitude and Longitude) for the entire path. The null hypothesis of the Getis-Ord General G statistic stipulates that there is no spatial clustering of participants' physiological responses. An incremental spatial autocorrelation was conducted to determine the optimum scale of the analysis[34]. The threshold distance of 11 m and 12.37 m was obtained for the LF/HF and PhasicMax measures, respectively. The resulting z-scores of the Getis-Ord General G statistic for the LF/HF and PhasicMax measures were 2.595 ($p < 0.01$) and 7.890 ($p < 0.01$), respectively. The spatial clustering analysis confirms that multiple participants' physiological responses are spatially associated and possess some common characteristics. The result implies that collective participants' physiological responses are indicative of an environmental condition. A hotspot analysis was conducted on the LF/HF and PhasicMax measures using a threshold distance of 11 m and 12.37 m to determine the environmental conditions that triggered a common physiological response among multiple participants. The hot spot analysis result for LF/HF and PhasicMax measures are presented in Figure 4c and Figure 4d, respectively. The hot spots are locations on the path with statistically significant high physiological response clusters. The cold spots are locations on the path with statistically significant low physiological response clusters.

Spatiotemporal analysis: Because the field data collection was conducted for only ten days and some of the participant's physiological responses were corrupted or abnormal, this study only demonstrated the effectiveness of the space-time pattern mining using the LF/HF measure. The result of the space-time pattern mining based on LF/HF measure with a threshold distance of 11 m and a time interval of one day is presented in Figure 4e. Several clusters of high physiological responses (hot spot) and low physiological responses (cold spot) were detected on the path. These hot and cold spot locations on the path are further categorised based on their occurrence over time. A consecutive hot (or cold) spot is a location with a single uninterrupted run of statistically significant hot (or cold) spot bins in the final time-step intervals. A sporadic hot (or cold) spot is a location that is an on-again then off-again hot (or cold) spot. An oscillating hot (or cold) spot is a statistically significant hot (or cold) spot for the final time-step interval that has a history of also being a statistically significant cold (or hot) spot during a prior time step. A consecutive hot (or cold) spot is a location with a single uninterrupted run of statistically significant hot (or cold) spot bins in the final time-step intervals. There were seven consecutive hot spots, four sporadic hot spots, 59 oscillating hot spots, two consecutive cold spots, 51 sporadic cold spots, 75 oscillating cold spots, and 217 spots with no pattern detected on the path.

Discussion

A comparison of older adults' physiological-environmental interactions, older adults' perceived stress assessments, and observers' path audit

The authors compare older adults' physiological-environmental interactions with the older adults' perceived stress assessments and the observers' audits of the path condition to confirm how well the elderly-centric sensing can represent the older adults' interaction with the built environment. A comparison of perceived stress, expert path audit, and detected hot and cold spots on the path is presented in Figure 4.

Segment A (an alley with several path obstructions) was perceived as stressful by the participants. Segment A's environmental condition was rated as poor by the auditors, and segment A was detected as a statistically significant cold spot, corresponding to physiological stress. The results across the three different assessment approaches confirm one another. The PhasicMax measure provided a more accurate representation of this segment with a higher confidence level than the LF/HF measure. The participants perceived segment B (a wide street) as non-stress. The auditors rated it as moderate, and half of segment B was detected as a statistically significant cold spot, corresponding to physiological stress. Participants had to cross a street in segment B; this street has vehicles parked along its shoulders. The anticipation of an approaching vehicle while crossing the street and having their field of view limited by the parked vehicles could have resulted in physiological stress. Because this occurrence is time-dependent, it could easily be missed during the path audit or while the participant reported their perceived stress. A review of the spatiotemporal analysis indicates a sporadic cold spot for parts of segment B immediately after the crossing, implying that the older adults experienced physiological stress on some days and were not stressed on other days.

Segment C was perceived as stress, the environmental condition at segment C was rated as moderate, and parts of segment C were detected as a statistically significant cold spot (physiological stress) and hot spot (non-physiological stress) based on the LF/HF measure and cold spot (physiological stress) based on PhasicMax measure. Segment D was perceived as stress by the participants, rated as good by the auditors and was only detected as a significant cold spot (physiological stress) based on the LF/HF measure. Segment D is a crosswalk with traffic signals. Although the crosswalk was rated as good, it was perceived as stress and experienced as physiological stress. A plausible explanation for such responses could be the waiting time at the traffic light, which was about 68 sec. The spatiotemporal analysis further indicates a sporadic cold spot on the crosswalk, suggesting that the participants were stressed on the days with a longer waiting time for the traffic signal to turn green and non-stressed on the days the waiting time is shorter. This is another time-dependent occurrence that was not captured in the observers' path audit.

The participants perceived segment E (an ongoing construction site) and segment F (an alley with path obstructions) as stressful, and the auditors' rated them as poor. Segments E and F were detected as statistically significant (95% confidence level) physiological stress spots by the PhasicMax measure. The authors observed that all the segments that were perceived as stressful and rated as poor only resulted in physiological stress when the data source is from the SCR (PhasicMax) with a 95% confidence level. Physiological data sourced from the heart rate (LF/HF) mostly misclassified such segments or detected them with a 90% confidence level. This indicates that segments rated as poor conditions have more pronounced effects on older adults' SCR than heart rate measures.

Physiological data sourced from the heart rate (LF/HF) is more indicative of the path conditions perceived as high stress or low stress than the data source is from the SCR (PhasicMax). For instance, segment G (a green space) was perceived as non-stress by the participants, and the environmental condition of segment A was rated as good by the auditors. Segment H (subway with graffiti) was perceived as high-stress and rated as moderate. Both heart rate and SCR data sources detected segment G as non-stress, consistent with the perceived and path audit assessments. However, only the heart rate (LF/HF) measure was able to detect segment H as stress at a 90% confidence level.

Overall, the older adults' perceived assessment of the path, the observers' path audit and the assessment based on physiological responses confirm one another more than they contradict. These contractions are expected because all of these assessment methods have inherent limitations. For instance, the older adults' perceived assessment is subjective; they could rate the mere presence of a gas station as stressful with a high-intensity rating, although the gas station may not distress the older adult. Although the observers' path audit is objective, they cannot adequately distinguish between an environmental condition that is stressful for a person and not stressful for another person. Therefore, it is expected that the perceived, objective, and physiological response based assessments should have some contradictions. Despite the contradictions, these methods can complement one another and improve the assessment of the built environment for older adults.

Collective sensing can address individual variability

This study shows that the relationships between older adults' physiological responses and environmental conditions are less apparent at the individual level. An individual's pace, walking behaviour, level of observation, physical characteristics and gender influenced their physiological responses to stress and non-stress environmental conditions. The physiological response data source (i.e., the related organ) and time-dependent environmental factors also contributed to the variability in older adults' physiological responses. The variability in older adults' physiological responses is what motivated this study. Assuming there was no individual variability (which will be the case when sensors are attached to mobility aids), an environment's condition can be determined by using the intensity of older adults' physiological response. Using the intensity of older adults' physiological responses to represent their interaction with the environment would be misleading in this study. This study shows that using collective sensing (aggregating multiple participants' physiological responses) can accommodate individual variability and capture any normality in the data, which is indicative of an environment's condition.

Limitations and future directions

The results should be interpreted with these limitations in mind. This study used a predetermined walking path for data collection; restricting older adults to a particular path may affect how they interact with the environment. The study was based on a small sample size, and the analysis was conducted for a limited number of days. The next phase of this study will be conducted in an elderly neighbourhood with more diverse participants without restricting older adults to a specific path. With these established relationships in older adults' physiological responses, future studies should harness machine learning to optimise the detection of older adults' stressful interactions with the built environment.

Conclusions

This study examines whether older pedestrians' physiological reactions are indicative of urban built environment stressors. The results revealed that collective EDA and HR responses are useful indicators of older adults' reactions to stress and non-stress built environment conditions. Older adults reacted somewhat differently to the same environmental conditions. These differences in responses were due to personal factors, the physiological response data source (i.e., the related organ), and time-dependent environmental factors. As a result of the differences in older adults' physiological responses to the same environmental condition, it is recommended that municipal officials, policymakers and urban planners should rely on collective participants' physiological responses to assess an environmental condition. This recommendation is supported by the results from this study which confirms that collective participants' physiological responses are spatially and temporally associated and possess some common characteristics. In general, the older adults' perceived assessment of the path, the observers' path audit, and the path assessment based on physiological responses confirm one another more than they contradict. Current advances in machine learning intelligence will be harnessed in future studies to optimise the detection of older adults' stressful interactions with the built environment.

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Table 1. A comparison of physiological responses to stress and non-stress environmental conditions.

Participant	Environmental condition	LF/HF Descriptive statistics Mean (SD)	LF/HF Descriptive statistics Median	LF/HF Test statistics Z	LF/HF Test statistics p	PhasicMax Descriptive statistics Mean (SD)	PhasicMax Descriptive statistics Median	PhasicMax Test statistics Z	PhasicMax Test statistics p
1	A	1.924 (1.301)	1.564	-1.399	.162	0.990 (0.692)	1.082	-12.035	.000**
	B	2.787 (3.164)	1.432			0.360 (0.420)	0.136		
2	A	1.938 (0.799)	1.979	-1.248	.212	0.277 (0.150)	0.256	-2.694	.007*
	B	1.537 (1.331)	1.117			0.315 (0.204)	0.284		
3	A	2.708 (2.209)	3.870	-2.341	.019*	0.547 (0.403)	0.490	-9.712	.000**
	B	1.964 (1.683)	1.429			0.365 (0.258)	0.324		
4	A	2.211 (2.616)	1.132	-2.498	.013*	0.130 (0.789)	0.126	-1.376	.169
	B	2.479 (1.765)	1.987			0.117 (0.085)	0.100		
5	A	1.753 (1.951)	1.027	-2.016	.044*	0.108 (0.492)	0.997	-2.242	.025*
	B	1.990 (2.838)	1.015			0.091 (0.044)	0.083		
6	A	2.335 (2.505)	1.254	-2.957	.003*	0.281 (0.298)	0.166	-1.882	.060
	B	1.984 (2.548)	1.172			0.237 (0.187)	0.177		
8	A	6.764 (13.119)	2.027	-0.155	.877	0.053 (0.036)	0.039	-0.751	.453
	B	4.366 (6.606)	2.212			0.059 (0.052)	0.040		
9	A	2.473 (1.600)	2.079	-0.508	.611	13.316 (7.435)	15.532	-11.035	.000**
	B	3.671 (3.920)	2.413			8.476 (5.741)	6.724		
10	A	4.768 (6.313)	1.929	-2.326	.020*	0.335 (0.169)	0.300	-3.588	.000**
	B	2.462 (2.562)	1.487			0.388 (0.175)	0.355		
Collective response	A	2.997 (5.475)	1.621	-3.862	.000**	1.730 (4.714)	0.201	-5.665	.000**
	B	2.541 (3.370)	1.428			0.996 (2.966)	0.157		
BMI > 24.9	A	2.719 (3.475)	1.538	-2.940	.003*	2.723 (6.031)	0.226	-1.608	.108
BMI < 24.9		3.386 (7.400)	1.683			0.406 (0.538)	0.158		
BMI > 24.9	B	2.436 (2.730)	1.497	-0.201	.841	1.635 (0.184)	0.131	-4.958	.000**
BMI < 24.9		2.669 (4.012)	1.340			0.244 (0.288)			
Female	A	3.041 (6.194)	1.673	-3.218	.001*	2.549 (5.759)	0.208	-7.217	.000**
Male		2.925 (4.006)	1.389			0.312 (0.307)	0.180		
Female	B	2.784 (3.760)	1.544	-1.381	.167	1.399 (3.617)	0.160	-0.479	.632
Male		2.108 (2.476)	1.251			0.252 (0.221)	0.153		

Note. A = non-stress environmental condition; B = stress environmental condition; Test statistics = Wilcoxon signed-rank test; SD = standard deviation; BMI = body mass index. *$p < .05$. **$p < .001$.

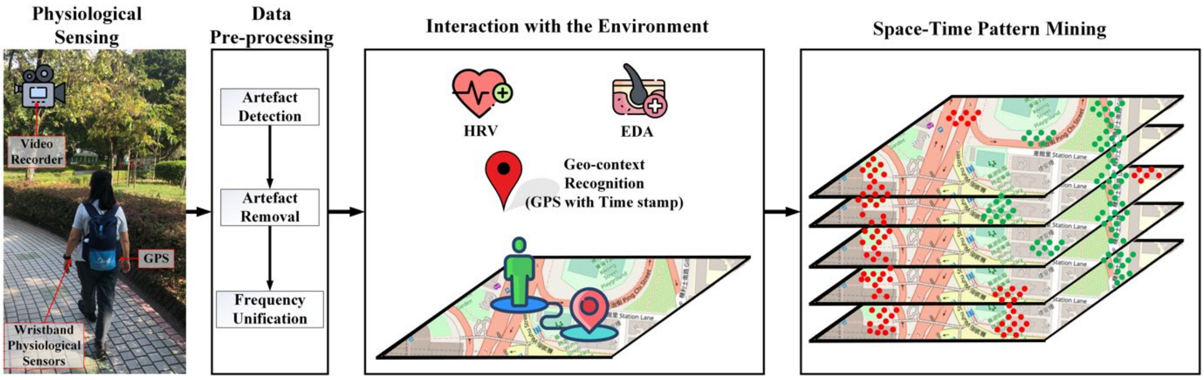

Figure 1. Overview of the study. HR = Heart rate; EDA = Electrodermal activity.

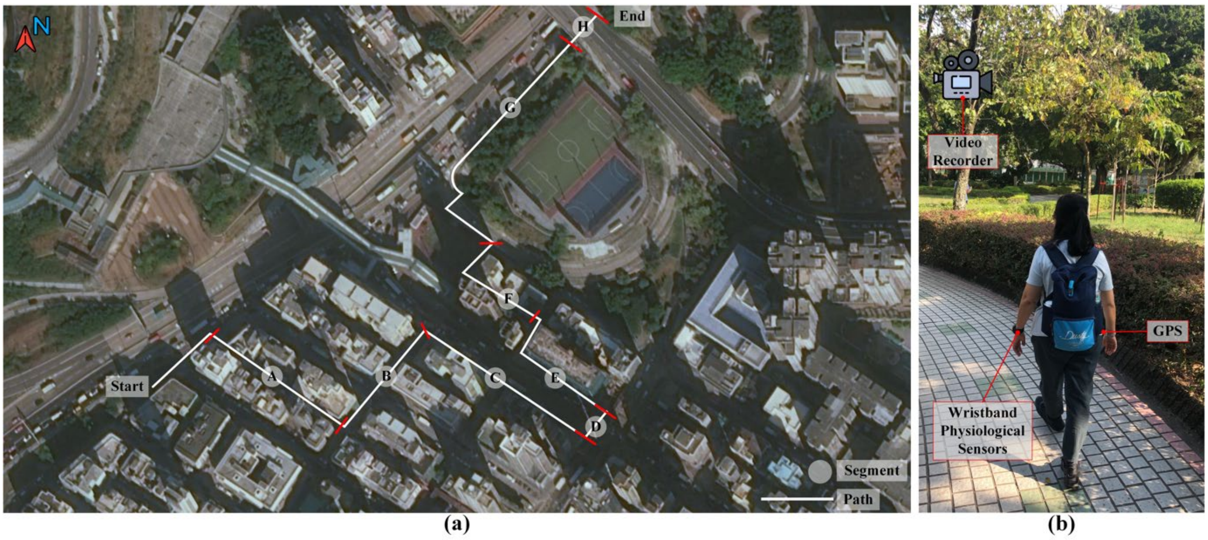

Figure 2. Field experiment overview. (a) Predefined path for the environmental walk. (b) An older adult with wearable sensors during the environmental walk.
Note. Basemap data copyrighted Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community. Photographs by authors.

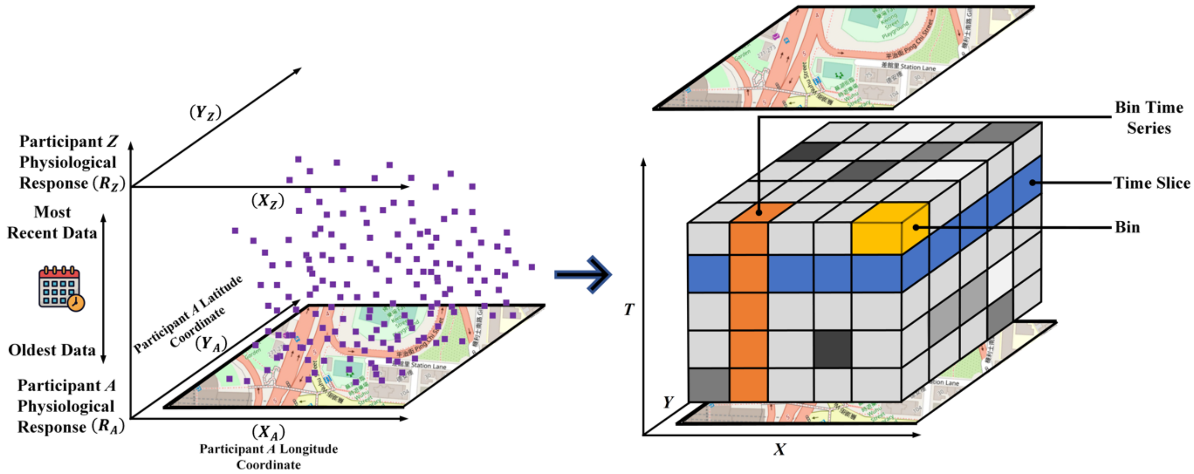

Figure 3. Aggregating participants' physiological responses into space-time bins with GPS coordinates (adapted from Esri, 2020).

Figure 4. Comparison of perceived stress, expert path audit, and detected hot and cold spots on the path. (a) Perceived stress and non-stress locations reported by participants. (b) Path audit by observers. The environmental condition was rated as poor, moderate or good. F = Rating for functionality; S = Rating for safety; A = Rating for aesthetics; O = Overall rating of path segment. (c) Spatial clusters of physiological responses based on LF/HF measure. (d) Spatial clusters of physiological responses based on PhasicMax measure. (e) Spatiotemporal clusters of physiological responses based on LF/HF measure.

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