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Detecting stressful older adults-environment interactions to improve neighbourhood mobility: A multimodal physiological sensing, machine learning, and risk hotspot analysis-based approach

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ABSTRACT

Not only is the global population ageing, but also the built environment infrastructure in many cities and communities are approaching their design life or showing significant deterioration. Such built environment conditions often become an environmental barrier that can either cause stress and/or limit the mobility of older adults in their neighbourhood. Current approaches to detecting stressful environmental interactions are less effective in terms of time, cost, labour, and individual stress detection. This study harnesses the recent advances in wearable sensing technologies, machine learning intelligence and hotspot analysis to develop and test a more efficient approach to detecting older adults' stressful interactions with the environment. Specifically, this study monitored older adults' physiological reactions (Photoplethysmogram and electrodermal activity) and global positioning system (GPS) trajectory using wearable sensors during an outdoor walk. Machine learning algorithms, including Gaussian Support Vector Machine, Ensemble bagged tree, and deep belief network were trained and tested to detect older adults' stressful interactions from their physiological signals, location and environmental data. The Ensemble bagged tree achieved the best performance (98.25% accuracy). The detected stressful interactions were geospatially referenced to the GPS data, and locations with high-risk clusters of stressful interactions were detected as risk stress hotspots for older adults. The detected risk stress hotspot locations corresponded to the places the older adults encountered environmental barriers, supported by site inspections, interviews and video records. The findings of this study will facilitate a near real-time assessment of the outdoor neighbourhood environment, hence improving the age-friendliness of cities and communities.

1. Introduction

The global population is ageing; the proportion of the global population aged 65 years or over (referred to as older adults in this study) is projected to increase from 9.3% in 2020 to 16% in 2050 [1]. Globally, one in six people is expected to age 65 years by 2050 [1]. With the changing age structure of the projected population, many countries are confronted with unprecedented challenges. An effective local approach for responding to population ageing is by creating environments that are inclusive and accessible to promote active ageing [2,3]. The Age-friendly Cities and Communities (AFCC) concept was proposed in pursuit of developing communities and cities that support active ageing [4]. The WHO proposed eight groups of features to promote active ageing: outdoor spaces and buildings; transportation; housing; social participation; respect and inclusion; civic participation and employment; communication and information; and community supports and health services [2]. Other concepts similar to the AFCC include the elder-friendly community [5–7]; liveable community [8], lifetime neighbourhood [9] and positive ageing framework [10]. All these AFCC concepts share a common aim to develop cities and communities that support active ageing [11].

The AFCC features broadly span from the physical environment to the social environment [11]. However, this study focuses on the outdoor environment, which is one of the key features of the city and community's physical environment that strongly influence personal mobility, safety from injury, security from crime, health behaviour and

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social participation [2,12,13]. In this research, the outdoor environment, built environment, and physical environment are used interchangeably.

Not only is the global population ageing, but also the built environment infrastructure in many cities and communities are approaching their design life or showing significant deterioration [14]. This phenomenon is referred to as "double ageing" [15]. Most of the infrastructure in the developed economies are aged 40 years or more [16]. Ageing built environment infrastructure with defects are likely to result in environmental barriers with excessive demands (an environmental barrier is an environmental condition or physical feature that can impede an individual's mobility [17] [18,19]. Research has shown that older adults residing in areas with environmental barriers, such as poor sidewalk conditions, high hills, and heavy traffic, are at a greater risk of reporting mobility limitations [17,20]. An environmental barrier is relative to a person's functional capability [21,22]; when the demands of an environmental condition or physical feature meet a person's functional capability, the person achieves successful mobility. Conversely, when the demands of the environmental condition or physical feature exceed a person's functional capability, the person experience stress and/or their mobility is limited [21,23–25]. Stress is a relationship between a person and the environment; it is experienced when demands tax or exceed the person's capability [26]. People with declined functional capacity, such as older adults, must contend with many environmental barriers that may result in stress and/or hinder older adults' participation in outdoor activities [27,28]. This study aims to identify such environmental barriers as a means to reshape our cities and communities to be more inclusive and accessible to people of all ages and abilities. In this research, the term detecting older adults' stressful interactions means detecting the stress of older adults while interacting with the built environment.

1.1. Assessing the built environment to promote mobility

Since the 1980s, urban planners and travel behaviour researchers have studied how the built environment affects people's outdoor physical activities, recreational behaviours, and quality of life [29,30]. In recognition of the importance of physical activity, planners have developed conceptualisations of community design such as walkability, that is, the extent to which the built environment supports and encourages mobility by walking [31]. Mobility is defined as the ability to achieve access to the desired place [17]. Conceptual models on the built environment and mobility postulate that mobility is affected by different built environment attributes [32,33]. To understand the effect of the built environment on mobility, it is of paramount importance to develop a high-quality assessment approach [30]. Of central concern among the active living researchers is developing accurate and efficient built environment assessment approaches [29,30]. Four categories of built environment assessment approaches are being used: perceived environment assessment approach, systematic observational assessment approach, Geographical information systems (GIS)-based assessment approach, and bodily response-bases assessment approach.

The perceived (also known as self-report) environment assessment approach often requires untrained raters to judge the extent to which the built environment promotes or hinders their mobility [29]. The perceived environment assessment approach is mainly collected using interviews or self-administered questionnaires [30,34]. The systematic observational assessment approach, also known as environmental audit, often requires trained observers to quantify the attributes of the built environment. Trained observers use predefined protocols or tools to assess the built environment attributes as it is directly observed (in-person observation) [30,35]. These audit tools have enabled a systematic and objective assessment of the built environment. The GIS-based assessment often relies on archived (existing) data that have spatial reference to assess the built environment [36]. Data such as infrastructure-based data (e.g., air quality and sound level), user-generated data (e.g., GPS) and street view imagery (e.g., Google Street View, Google Earth, and Bing Map) are often used to audit the built environment [37–39]. GIS-based assessment enables an objective assessment of the built environment dispersed across a large area [30]. The fourth category of assessment approach involves data collected from users' direct bodily responses to assess the built environment objectively and continuously [40–44]. The bodily responses (i.e., physiological, behavioural, or cognitive responses) collected using sensing technologies are spatially matched with GPS data to assess the built environment.

Each of the built environment assessment approaches has its own advantage and disadvantage, which could affect its effectiveness. Because the perceived environment assessment involves interviews or self-administered questionnaires, its main drawback is declining response rates [30]. Also, interviewing or administering questionnaires to older adults might obstruct their daily lives; especially in large-scale neighbourhood assessment that takes a longer period to complete. Although the observational assessment approach is objective, it involves in-person observation, which is time-consuming and costly [30]. Observational assessment demands investment in staff, training of observers, and transportation to the assessment site, among others. Because this approach is time-consuming, labour intensive and costly, it may limit the scope and frequency of conducting neighbourhood assessments. Although the GIS-based assessment can provide an objective, less obstructive, less labour intensive, less time-consuming, and large-scale assessment of the built environment [45], it is inefficient in detecting older adults' environmental barriers. Because an environmental barrier is relative to an individual's capability, the GIS-based approach cannot adequately distinguish between an environmental condition that is a barrier for one person and not a barrier for another person [21,22]. Sensing people's direct bodily responses to the environment can detect such environmental barriers that could not be detected using the GIS-based or observational assessment approach [40,42,46,47]. The bodily response-based assessment provides a continuous assessment of the built environment and is less obstructive depending on the sensing technology adopted. The major limitation of the GIS and bodily response-based assessments is the hardware cost. However, the decrease in size, cost and miniaturisation of the sensors have made them more pervasive in recent times, and they are now embedded into wearable devices [48].

1.2. Wearable technology for older adults in a real-world ambulatory setting

The human experience in the environment is the human state of being affected by the surrounding environments [49]. Signals for inferring changes in demanding environmental conditions are regulated by the autonomic nervous system (ANS) [50,51]. The ANS consist of the sympathetic and parasympathetic nervous systems that usually act involuntarily to regulate human response to stress [42,50]. When the body is stressed, the ANS provoke responses in humans which are reflected in the physiological, behavioural and cognitive signals [51,52]. 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. Behavioural signals are somewhat voluntary actions that can be externally observed. The cognitive signals relate to the activities of the brain or mental state [52].

Current generation wearable technology with wireless sensors has enabled non-invasive real-time sensing of a person's physiological, behavioural, and cognitive state. Researchers are harnessing these wireless sensors to advance the frontiers of knowledge about human-environment interaction in ambulatory naturalistic settings. For example, pedestrians' behaviour, mainly gait patterns, has been continuously monitored using inertial measurement unit (IMU) sensors to assess neighbourhood walkability [40,46,53]. When pedestrians walk on a defective sidewalk (for example, broken pavement, an uneven sidewalk, or loose brick), their gait becomes unstable and imbalanced.

As a result, recent studies have attempted to monitor pedestrians' gait as a means of assessing the environmental condition. Although this is a promising approach to detecting defects in sidewalks, it may be ineffective when the gait data is collected from older adults due to the prevalence of gait disorder among people aged over 60 years [54]. Older adults exhibit diverse abnormal gait responses, which makes it unreliable when computing the common gait among multiple older pedestrians to detect environmental defects [55].

The activation of the human brain has been continuously monitored using wearable electroencephalogram (EEG) sensors to detect stressful environmental conditions [47,56]. The brain's activities are measured by attaching electrodes at specific points on the skin of the head to make good contact with the scalp [57]. However, because current EEG sensors require good contact with the scalp, their effectiveness can be impacted in an ambulatory, real-world setting. For example, recent studies reported stability issues and temporary dysfunction of an EEG headset while monitoring pedestrians' brain activation in an ambulatory outdoor environment [55,58]. To accurately and reliably monitor older adults' stress due to environmental conditions, it is essential to use sensors that are stable in the wild.

In recent years, an increasing number of studies have measured human physiological signals from wireless sensors worn on the wrist. For example [41–43,59], and [44] monitored people's physiological response from wristband type sensors in ambulatory, real-world settings. These earlier studies prove that physiological signals can be monitored from wristband-type sensors in an ambulatory, real-world setting and can be extended to capture older adults' stressful environmental conditions. Older adults perceive wristband-type sensors as comfortable and easy to use, and, therefore, suitable for long-term use [60].

1.3. Multimodal physiological sensing and fusion

Photoplethysmogram (PPG) and electrodermal activity (EDA) are the commonly used physiological signals to reflect stressful human-environment interactions [41,42]. PPG is an optical and non-invasive method that measures the blood volume pulse from which heart rate variability (HRV) can be derived. HRV is a reliable indicator of the sympathetic and parasympathetic nervous system; it is of huge interest in studies of stress [61]. EDA is also known as Galvanic skin response. EDA measures the activation of the sympathetic nervous system non-invasively and is one of the most frequently employed signals for detecting physiological arousal and stress [62,63]. A stimulated sympathetic nervous system triggers variation in the eccrine sweat gland activity, thus changing the conductivity of the skin [63].

Specifically, previous studies have used one physiological modality (i.e., PPG or EDA) or one feature extracted from a physiological modality (mainly, heart rate extracted from PPG or mean EDA extracted from EDA) to understand people's interaction with the built environment [41,46,64]. Although these modalities and features are useful indicators of people's stressful interactions, relying on only one physiological modality or feature might not be enough when it comes to understanding stressful human-environment interactions in ambulatory, real-world settings because the informativeness of the modality or feature could be impacted by human variability (e.g., pace), sensor variability (e.g., sensor drift) and environmental condition (e.g., temperature). To improve the effectiveness of the bodily response-based assessment approach, this study adopts a multimodal information fusion technique.

Information about stressful human-environment interaction can be acquired among others from different types of sensors, under different conditions, from multiple participants or experiments. Each acquisition framework is termed a modality and is associated with one data set. A complete setup of the framework making use of multiple modalities for each data set to interact and inform each other is termed multimodal [52,65]. Multimodal fusion is a well-established technique. Its effectiveness is demonstrated by minimising the effects of incorrect data acquisition and providing complementary data (collective knowledge) that enhance the diversity of the system. Diversity helps improve the reliability, accuracy, robustness, uniqueness and generalisation of the system [65].

Multimodal information can be fused at three main hierarchical levels: signal level (raw) data fusion, feature level fusion and decision level fusion [66,67]. Signal level fusion is applied to data measuring the same signal property (commensurate data) directly. Feature level fusion is applied to combine data measuring separate signal properties (non--commensurate data). Decision level fusion is implemented at the highest level of abstraction from sensor data, and it is more appropriate when modalities have differences in time scale [48,66]. In this study, two different modalities (i.e., EDA and PPG signals) are measured in a synchronised time scale to represent stressful human-environment interaction. Feature level fusion strategy is the most appropriate for this study because the EDA and PPG signals measure different signal properties (i.e., the EDA measures signal property from the skin organ and the PPG from the heart organ). In this case, features extracted from sensor data are used to form a feature vector and combined using parametric or non-parametric machine learning algorithms to discriminate and represent the data into higher abstractions [48,66].

1.4. Built environment determinant of walking

The main evidence-based framework of physical environmental factors that may influence walking in the local neighbourhood was developed by Ref. [32]. Based on published evidence and policy literature, interviews with experts and a Delphi study [32], identified four built environmental domains: functionality, safety, aesthetics, and destination. Functionality relates to the physical attributes of the street and path that reflect the condition of the structural elements of the built environment [32,68]. Safety reflects elements of the environment that strengthen the feeling of safeness and increase the degree of comfort of the older pedestrians [32,68,69]. Aesthetics reflects elements of the environment that are visually interesting, and appealing on the human scale, and increase the attractiveness of the environment [32,68,69]. The destination domain relates to the availability of community and commercial facilities in the neighbourhood [32]. The built environmental domains and factors that contribute to each of these domains are presented in Table 1.

1.5. Environmental stress hotspot

Stress can be triggered by several factors [70]. Previous studies have successfully distinguished between stressful interactions due to the built environment from stress due to other stress factors by using hotspot analysis. Hotspot analysis is a spatial analysis technique for identifying clusters of spatial phenomena. Getis-Ord Gi* and kernel density estimation have been employed to detect environmental stress hotspots from people's physiological responses to the environment [41,58,64].

A neighbourhood with significant built environment infrastructure approaching their design life is more likely to have several environmental stress hotspots for older adults. Given the limited resources available to most cities and communities, it will be more beneficial to identify the stress hotspots that pose a higher risk to older adults. Such stress hotspots can be prioritised and alleviated to improve neighbourhood walkability for older adults.

1.6. Research objectives and significance

This research aims to develop and test a smart and more efficient approach to detecting older adults' stressful interactions with the environment. To achieve the aim, this study (1) sensed older adults' physiological reactions using non-invasive wearable wristband-type sensors to represent their interaction with the environment, (2) trained and tested machine learning algorithms to detect each older

Table 1
Built environment factors that may influence walking.

Domain	Element
Functionality	Path condition (wet and slippery streets)
	Path slope
	Path obstruction
	Major barriers (roadwork, steep staircases)
	Minor barriers (cracks, holes, bumps, parking meters)
	Street crowd
	Motor vehicles parked on footpath
	Hawkers and shops on streets
	Path width
	Path material
	Curb cut features
	Permeability
Safety	Pedestrian crossing
	Traffic load
	Traffic calming devices
	Streetlight
	Directional sign
	Presence of people
	Signs of crime/disorder
	Stray dogs/other animals
Aesthetics	Views
	Building attractiveness
	Attractive natural sights
	Streetscape
	Litter
	Graffiti
	Pollution (noise and air)
	Greenery
Destination	Transport-related
	Public open space
	Recreational
	Government/public services
	Public facilities
	Commercial destinations

Source: [32,68].

adult's stressful interactions from their multimodal physiological signals, location and environmental data, and (3) spatially matched the detected stressful interactions with GPS data and locations with clusters of risk stress hotspot were identified. The outcome of this study will be a multimodal data collection and computational approach that will enhance the effectiveness of the bodily response-based assessment of the built environment. More importantly, this study will enable urban planners to detect, prioritise and alleviate environmental stress hotspots that pose a higher risk to older adults.

2. Method

This research is designed to recreate the natural environment as realistically as possible to ensure ecological validity. Using an environment that is natural or normal to the participant has higher ecological validity. It is more likely to obtain a result representing everyday life; in that way, results are more generalisable to the target population and other environment settings [71–73]. However, examining naturalistic behaviour in natural settings makes it impossible to ensure that the outdoor environmental conditions (e.g., weather conditions) remain the same for each experiment day and for all participants. An overview of the research approach is depicted in Fig. 1.

2.1. Experiment design

Through the collaboration with the Institute of Active Ageing, Hung Hom, a 570 m walking path was selected in the neighbourhood of Hung Hom, Hong Kong. The path was selected because it consists of various potential environmental conditions that can hinder older adults' mobility; it is located in an old district currently undergoing urban renewal. The description of the path is presented in Fig. 2, Fig. 3, and Fig. 4. The Institute of Active Ageing is an interdisciplinary research and academic centre for the advancement of knowledge and practice to facilitate active ageing. Ten ambulatory older adults aged 65 and above were recruited through the networks of the Institute of Active Ageing to participate in the environmental walk. This experiment involves older adults self-reporting their experience (i.e., perceived assessment of the path). The prevalence of subjective cognitive decline among older adults could affect their assessment [74,75]. Therefore, the participants had to meet the recommended cut-off score for The Mini-Mental State Examination (MMSE) to be eligible to participate in this study. The MMSE is a quick, easy-to-use, acceptable, valid, reliable and widely used screening instrument for assessing cognitive functions both in clinical and research settings [76–78]. The MMSE comprises 11 questions and requires only 5–10 min to administer. The MMSE consists of two main parts. Part one examines the participants' oral responses focusing on the orientation, memory, and attention of the participants. Part two examines the participants' ability to name objects, follow verbal and written commands, write a sentence, and copy a complex polygon similar to a Bender-Gestalt Figure.

The Cantonese version of the MMSE (CMMSE) [79] was used to screen the older adults in Hong Kong. The CMMSE is readily comprehensible to the older adults in Hong Kong. The scale has been proven to have good reliability and validity to detect cognitive impairment among Hong Kong elderly [79,80]. A cut-off score of 19/20 is recommended as an indication of cognitive impairment among Hong Kong older adults. According to Ref. [79]; the educational level of the participants has a significant effect on the MMSE scores. In order to factor in this difference, three different cut-off scores were recommended: cut-off score ≥18 points for the illiterate elders, cut-off score ≥20 points with 1–2 years of education; and cut-off score ≥22 points with more than 2 years of education [80,81]. All of the ten participants scored above the recommended score for the test. The environmental walk was conducted in November 2019 between 10 a.m. and 4 p.m. The environment temperature ranges from 24°C to 29 °C, and the humidity ranges from 41% to 55%. The weather condition and the time to complete the walk for each

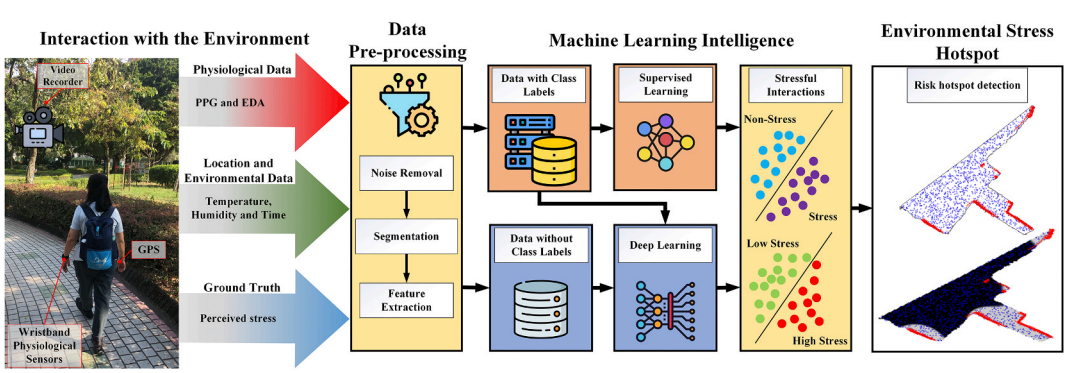
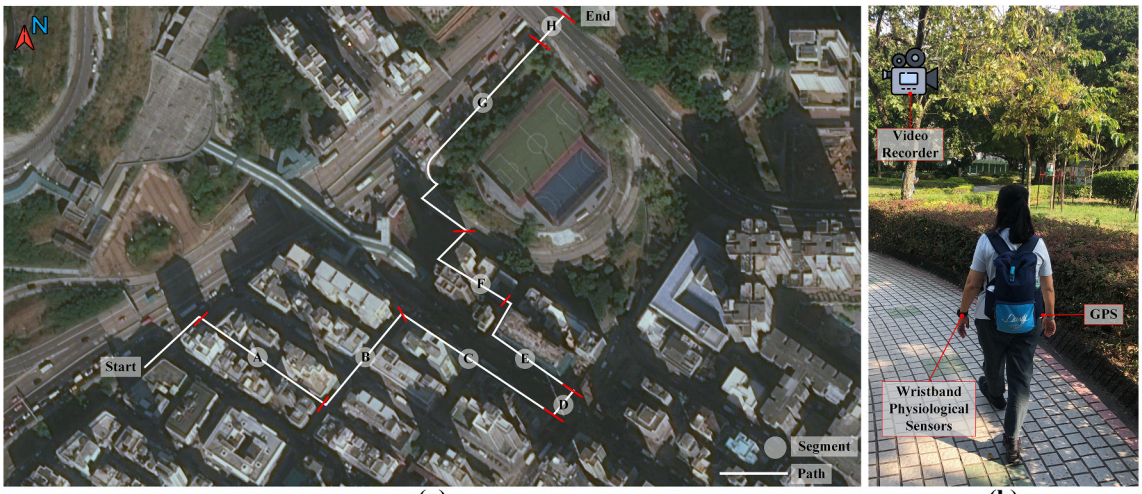


Fig. 1. Overview of the research.



(a) (b)

Fig. 2. Field experiment overview. (a) Predefined path for environmental walk. (b) An older adult equipped with wearable sensors. Participants walked through an alley (segment A), a street (segment B), a sidewalk beside a high traffic road (segment C), a pedestrian crossing with a traffic signal (segment D), a sidewalk beside a construction site (segment E), an alley (segment F), a green space (segment G), and a subway (segment H). Basemap data copyrighted Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Air bus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community. Photographs by authors. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

participant are provided in the online supplementary material. A shopping voucher was offered as compensation for participation.

Before the environmental walk, a practice session was held to demonstrate the wearable sensors to the participants and to familiarise the participants with the experimental procedures. The participants were also briefed on the definition of stress adopted in this study. The participants completed and signed an informed consent form after obtaining written and spoken information about the experimental procedures. The environmental walk was conducted in two stages: (1) physiological sensing; and (2) ground truth collection. During the first stage, the participants walked the path while equipped with wearable sensors for physiological sensing, location and environmental data collection. The participants walked the path from start to finish, as shown in Fig. 2, at a self-directed pace. Two researchers accompanied the participants. One of the researchers was responsible for providing directions if needed, and troubleshooting any technical malfunction with the wearable sensors. The other researcher recorded a video of the environmental walk and took notice of any abnormal activity or event.

During the second stage, the participants were asked to walk the same route without wearing the sensors. Instead, the participants were asked to identify locations where they experienced stressful interactions with the environment. The participants also stated the intensity of the perceived stress (low or high intensity). A researcher accompanied and assisted the participants to document their responses. Participants' responses from the second stage combined with the recorded video were used to label their physiological signals as (1) non-stress and stress; and (2) low-stress and high-stress. Note that none of the participants has previously experienced or is familiarised with the path. The walking path and experimental procedures were reviewed and approved by the Human Subjects Ethics Sub-committee of The Hong Kong Polytechnic University (Reference Number: HSEARS20190826002).

2.2. Data collection

Two biosensors—a PPG sensor and an EDA sensor—were used to recognise the physiological states of older adults. A commercial-off-the-shelf wearable, the Empatica E4 wristband, was selected for this study because it has both PPG and EDA sensors that synchronously measure and provide a continuous stream of PPG and EDA data. The E4 wristband is non-invasive and easy to use for older adults in everyday and outdoor conditions. All participants wore the E4 wristband on their non-dominant hands to minimise motion artefacts [82]. This wristband records the PPG signal at 64 Hz and the EDA signal at 4 Hz. Ambulatory, real-world measurements of physiological signals using non-invasive wearables are susceptible to external interferences such as motion artefacts, electrode popping, and environmental noise [83]. To suppress the external interferences in the physiological signal, the EDA signal was filtered using a Butterworth low-pass filtered with a cut-off frequency of 0.28 Hz and smoothed with a moving average filter to remove non-EDA related sensor readings. Note that the most valuable EDA signal information is typically below 0.28 Hz during low-intensity activities such as walking [84]. For the PPG, the authors first computed the instantaneous heart rate (at 1 Hz) from the inter-beat interval obtained from the PPG signal with a proprietary algorithm [85]. Artefacts and ectopic beats were detected and corrected using another proprietary algorithm [86].

In addition to the physiological data, location and environmental data were collected. GPS coordinates were logged using Qstarz BT-Q1000XT at 1 Hz. Generally, the infrastructure of the urban environment and season where the walking route is located is uniform. However, the experiment was conducted on different days and at different time-of-day, which may affect the participants' bodily responses. Therefore, the environment temperature (°C) and humidity (%) for each experiment day and time of day were recorded from the Hong Kong Observatory. Participants' PPG and EDA were recorded during a 10-min rest period for baseline measurement. Participants' PPG, EDA and GPS coordinates were recorded during the first stage of the environmental walk. Each participant's PPG and EDA were baseline normalised to reduce inter-individual variance.

2.3. Feature extraction

2.3.1. Physiological data

The filtered instantaneous heart rate signal and EDA signal were used for feature extraction. The best possible indicators of stress (physiological state) in this study would be a physiological feature that continuously fluctuated, proportional to the pedestrian's physiological state throughout the environmental walk. To extract the features with such characteristics, continuous calculations were conducted on each of the physiological signals at 1 s intervals throughout the entire duration of each pedestrian's walk on the path (to correspond to the 1 Hz GPS data). To create a continuous time series, Welch's periodograms [86] were calculated using 60 s windows of instantaneous heart rate data and

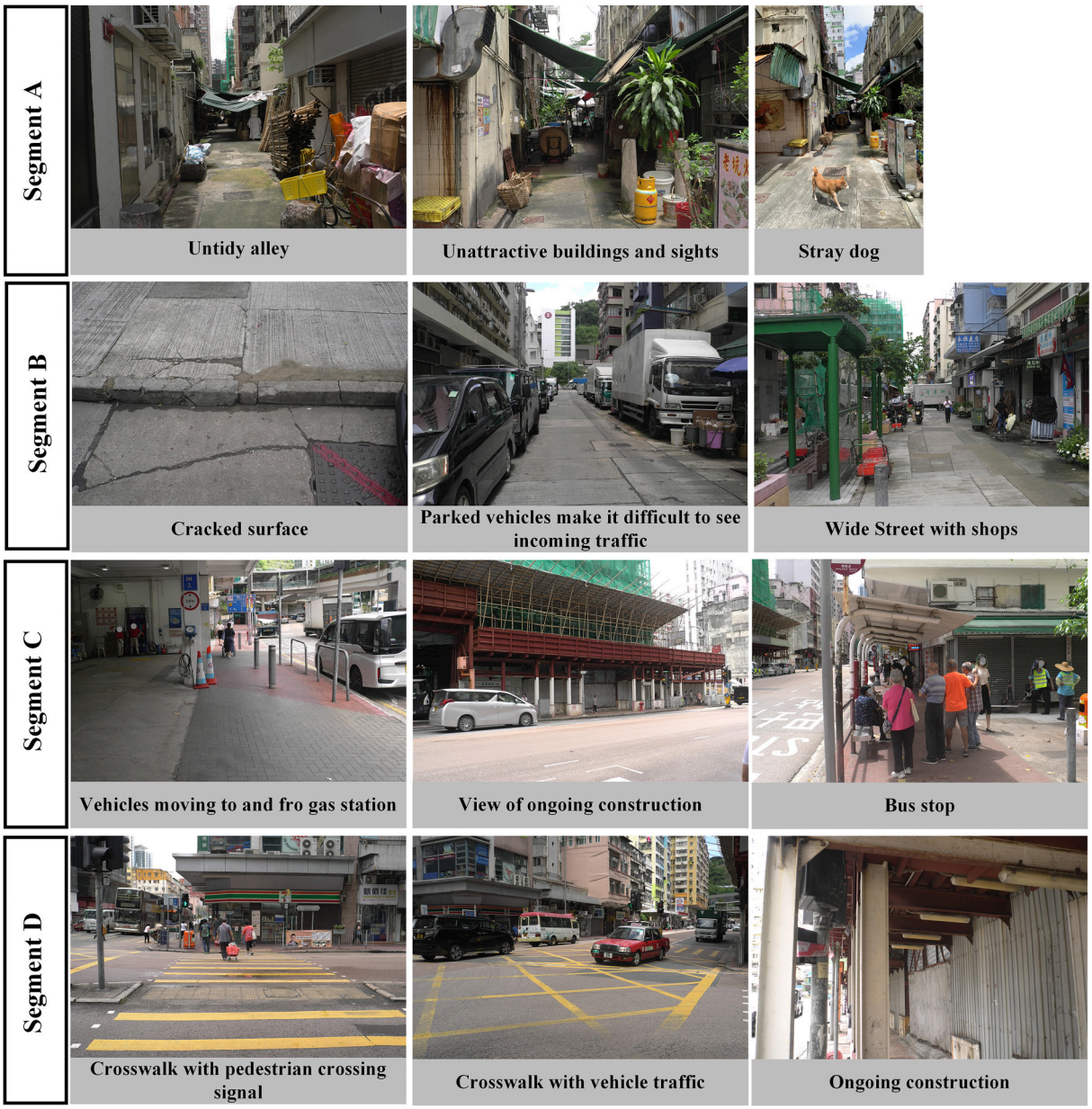


Fig. 3. Photo description of path segment A to D. Photographs by authors.

advanced by 1 s for each second of the entire pedestrian's walk. A total of 31 HRV features were extracted from the 60 s window. For the EDA signal, the authors first applied a continuous decomposition analysis to decompose the EDA signal into two components [87]: skin conductance response (SCR) and skin conductance level (SCL). The SCR and SCL were segmented into a continuous time series of 10 s windows and advanced by 1 s for each second of the entire pedestrian's walk. A total of nine EDA features were extracted from the 10 s window. The 60 s (for HRV) and 10 s (for EDA) windows were used because it is expected that the physiological effect of an environmental stressor would occur slightly after the pedestrians interact with the environmental stressor. Based on previous studies, a 60 s (for HRV) and 10 s (for EDA) physiological effect window is sufficient to fully capture the older adults' reaction to environmental stressors [88,89].

2.3.2. Location and environmental data

The time a participant was present at a location, the environment temperature and humidity were extracted as features. These features were important in this study because previous studies have confirmed that weather affects mood [90].

2.4. Feature selection

Feature selection was conducted to optimise the validation accuracy and to reduce the chances of overfitting the supervised learning algorithms. While there are various methods to select features, correlation-based feature selection (CFS) was used in this study. CFS ranks optimal subsets of features according to a heuristic evaluation function based on correlations. The CFS function (equation (1)) evaluates subsets of features that are correlated with the class label but independent of each other [91].

$$Merit_S = \frac{k\overline{r_{cf}}}{\sqrt{k + k(k-1)\overline{r_{ff}}}} \tag{1}$$

where $Merit_S$ is the heuristic merit of a feature subset S containing k features, $\overline{r_{cf}}$ is the average correlation value between feature and class labels, and $\overline{r_{ff}}$ represents the average correlation value between two

Fig. 4. Photo description of path segment D to H. Photographs by authors.

features (feature-feature intercorrelation).

2.5. Machine learning algorithms for feature fusion and stress detection

The selected features were fused using machine learning algorithms to detect (1) stress and non-stress samples from the collected data; and (2) low-stress and high-stress samples from the stress samples. The following supervised machine learning algorithms were tested: Decision Tree, Gaussian Support Vector Machine (SVM), k-Nearest Neighbour (KNN), and Ensemble bagged tree. These supervised machine learning algorithms were tested because previous studies have reported that they can detect stress from people's physiological data [92]. Recently, the automatic discovery of representative features through deep learning methods has been successfully used to analyse physiological signals in multiple modalities for several detection and prediction tasks [93]. A deep belief network (DBN) was also tested in this study to detect stress and high-stress samples.

k-fold cross-validation (k = 10) was conducted to evaluate the performance of the machine learning algorithms. k-fold cross-validation is a validation procedure using randomised subsets of data to estimate the robustness (i.e., accuracy and classification success) of a model when applied to new situations [94]. It is a computationally powerful and widely accepted validation procedure [95]. In general, as the value of k increases (i.e., varies from 2 to n – 1 fold subsets), the bias decreases, and the variance and computation time increases. In practice, the value of k = 10 is very common in machine learning because it produces validation results that suffer neither from excessively high bias nor very high variance [96]. This validation process involves partitioning the dataset into ten equal bins and performing ten separate rounds of learning experiments. Nine of the bins were employed during each round as a training dataset and the remaining one bin as a test dataset. Three performance indicators: accuracy, precision, and recall, were calculated to evaluate the performance of the machine learning algorithms. The definitions of the indicators are

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

where*TP* represent true positive, *FP* represent false positive, *FN* represent false negative and *TN* represent true negative. The trained algorithm with the highest accuracy, precision and recall was used for stress detection.

2.6. Identifying spatial clusters of risk stress hotspot

Spatial relative risk (SRR) is a well-understood concept and has been applied in spatial epidemiology to determine where spatial clustering is likely to occur [97–99]. The essential attribute of the SRR is its ability to estimate ratios of risks from two sample groups (e.g., case and control groups) without having access to their population denominators [100]. The estimator of SRR is a ratio of two kernel-estimated density functions of two distinct samples of point locations defined on a common spatial window [100,101]. Based on the definition of SRR, this study defined SRR stress hotspot as the ratio of kernel density estimates of stress samples and non-stress samples of point locations in a common study area (e.g., a neighbourhood). The statistical power of the SRR stress hotspot was computed to assess the probability of a stress hotspot occurring within a study area [97].

The focus here is on the locations where clusters of SRR high-stress hotspot is likely to occur. The detected high-stress samples (i.e., the case) and control samples (i.e., non-stress and low-stress samples) for each participant were associated with the corresponding GPS positions (Latitude and Longitude) for the entire path. Based on the case and control samples of point locations within the study window, the authors randomly generated simulated point locations (assuming complete spatial randomness) to reflect the expected study design at a resolution of (128 × 128 grid). The simulation-based approach was adopted to ensure realistic study power analyses [97,102]. The bandwidth calculation was based on the maximal smoothing principle [103]. The SRR function [101]—originally developed to study the spatial variation of larynx and lung cancer in the UK [104,105]—has been successfully employed to detect local clustering in many spatial analyses [97,106,107]. The SRR function was used to estimate the SRR high-stress hotspot for each grid cell within the simulated data area. The statistical significance of the spatial clustering of each grid cell was tested—the alpha level was set to 0.05. The authors repeated these steps for 10,000 iterations (recommended for power calculation [[97]]). The statistical power (power threshold of 0.8) of the SRR high-stress hotspot at each grid cell was calculated as the proportion of rejected null hypotheses from the simulated 10,000 iterations.

3. Results

The demographic information of the ten participants is presented in Table 2. Participant seven's (Table 2) data was not analysed due to missing physiological data during the environmental walk. A total of 5518 geo-located physiological data observations were collected from the participants.

3.1. Performance of the stress detection algorithms

Given the rich, multimodal nature of the data collected, careful feature extraction is critically important. First, an initial set of 43 features was extracted from the physiological data, location and environmental data based on a literature review. Feature selection was conducted using CFS. A complete list of the extracted features and results of the CFS is presented in the online supplementary material. The highest-ranked feature subset with at least one feature from each modality (i.e., PPG data, EDA data, location and environmental data) was selected. The selected feature subset contains 12 features, which are listed in Table 3.

Table 2
Participants' demographic information.

Participant	Gender	Age (years)	Height (cm)	Weight (kg)	Body Mass Index (kg/m^2)
1	Female	65	162.0	57.0	21.7
2	Female	65	158.0	62.0	24.8
3	Male	66	160.0	71.0	27.7
4	Female	75	161.1	67.5	26.0
5	Male	68	173.0	83.0	27.7
6	Female	72	157.5	54.4	21.9
7	Female	71	152.4	60.5	26.0
8	Female	66	157.5	59.0	23.8
9	Female	66	154.9	60.0	25.0
10	Male	66	175.0	77.7	25.4
Mean		68	161.1	65.2	25.0
SD		3.5	7.4	9.4	2.1

Note. SD = standard deviation.

The distribution of the collected data across the class samples was unequal [(3691 samples were labelled as stress while 1827 samples were labelled as non-stress), (1938 samples were labelled as low-stress while 1753 samples were labelled as high-stress)]. The high number of stress samples compared to the non-stress samples is probably because the path is located in an old district and it is currently undergoing urban renewal. To avoid an imbalance classification, the authors randomly under-sampled the majority class to make the classes have equal distribution. The under-sampling was repeated 20 times, resulting in 20 random train/test splits of the equally distributed data. 10-fold cross-validation was conducted to evaluate the performance of the machine learning algorithms. The average performance indicators of each machine learning algorithm over the 20 random train/test split data were computed. The stress detection performance of the algorithms deployed in this study is summarised in Table 4. The result indicates that the Ensemble bagged tree algorithm outperformed the other algorithms, achieving a classification accuracy of 98.13% (for detecting stress and non-stress samples) and 98.25% (for detecting low and high-stress samples). The confusion matrix of the best performance Ensemble bagged tree algorithm among the 20 random train/test split data is depicted in Fig. 5.

Table 3
Selected 12 features.

Modality	Feature	Description [unit]
PPG data	HR	Instantaneous heart rate values [1/min]
	Mean RR	The mean of RR intervals [ms]
	Min HR	Minimum heart rate computed using five beat moving average [1/min]
	Max HR	Maximum heart rate computed using five beat moving average [1/min]
	HF (Hz)	Absolute power of high frequency band (0.15–0.4 Hz) [Hz]
	LF (log)	Natural logarithm transformed value of absolute power of low frequency band (0.04–0.15 Hz) [log]
	HF (n.u.)	Power of high frequency band (0.15–0.4 Hz) in normalised units [n.u.]
	Total power	Total spectral power [ms^2]
EDA data	PhasicMax	Maximum value of phasic activity within response window [muS]
	Tonic	Mean tonic activity within response window of decomposed tonic component
	Global Mean	Mean skin conductance (SC) value within response window
Location and environmental data	Time	Time of day [Unix time]

Table 4
Performance of the stress detection algorithms.

	Algorithm	20 trains average score		
		Accuracy (%)	Precision (%)	Recall (%)
Detecting non-stress and stress samples	Decision tree	92.16	93.36	90.77
	Gaussian SVM	95.47	94.31	96.79
	KNN	95.96	96.00	95.90
	Ensemble bagged tree	98.13	98.59	97.65
	DBN	83.38	82.58	84.61
Detecting low and high-stress samples	Decision tree	89.45	90.61	88.56
	Gaussian SVM	95.94	96.83	95.14
	KNN	96.54	97.26	95.87
	Ensemble bagged tree	98.25	98.30	98.20
	DBN	73.76	75.01	74.08

3.2. Spatial clusters of risk stress hotspot

Given the impressive performance of the Ensemble bagged tree algorithm, the authors deployed the best performance Ensemble bagged tree algorithm (the confusion matrix is depicted in Fig. 5) to classify each of the participant's collected data into (1) non-stress and stress; and (2) low-stress and high-stress. The deployed algorithm detected 66.35% of stress samples and 26.73% of high-stress samples from all participants' data. The detection result for each participant is shown in Table 5. The detected high-stress samples (i.e., the case) and control samples (i.e., non-stress and low-stress samples) for all participants were geographically referenced with their corresponding GPS coordinates. The first iteration of the simulated randomly generated point-level physiological data is shown in Fig. 6. The proportion of the significant SRR high-stress hotspot clusters for the 10,000 simulation iterations is presented in Fig. 7(a). The areas within the study area that are sufficiently powered to detect spatial clustering of a high-stress hotspot are shown in Fig. 7(b). These results demonstrate that the path for the environmental walk has some real spatial clusters of high-stress hotspots.

3.3. Examination of spatial clusters of risk stress hotspot

Upon examining the risk stress hotspot locations, the authors identified some environmental barriers relating to the functionality, safety, and aesthetics of the path conditions (Fig. 8 and Fig. 9). Environmental barriers A1, S1, and F1, were identified in risk stress hotspot 1. The authors found that the risk stress hotspot 1 was mainly caused by a restaurant. Old gas cylinders, broken furniture, and several old or broken restaurant equipment were found outside the restaurant and on the path (barriers A1 and F1). The path surface was wet (barrier F1). Some of the participants were observed taking precautionary measures by slowing their pace. About three dogs were spotted in this location during the environmental walk (S1). All the participants reported that they felt stressed while walking through this spot. For instance, one of the participants commented that she would not have been able to walk this segment of the path alone. "Why would someone eat here?" one of the participants asked rhetorically.

Risk stress hotspot 2 consists of environmental barriers A2-A5, S2–S4, and F2–F6, extending from segment C to F as shown in Figs. 8 and 9. This spot has a gas station and a bus stop beside path segment C. The authors noticed that some of the participants interacted with vehicles entering or exiting the gas station; this interaction could be stressful, especially if not perceived in advance (barrier S2). Another group of participants mentioned that they realised it was a gas station from a distance, and they were hoping they would not encounter any car entering or exiting the gas station. This anticipation about what will happen in the near distance could have resulted in stress (barrier S2). Path obstructions such as traffic cones and bollard barricades were identified on the sidewalk beside the gas station (barrier F2). The participants that engaged in the environmental walk in the midmorning remarked that the bus stop was too crowded and was stressful to navigate (barrier F3). The view from this spot is a bamboo scaffolding with screen nets on a high-rise building, which at first glance, seems a little frightening (barrier A2). Although the pedestrian crosswalk (segment D) has traffic calming devices (traffic signal and traffic island), it was still detected in the risk stress hotspot 2. Some of the participants mentioned that the waiting time (which was about 68 s) at the traffic signal was stressful (barrier S3). Segment E—an ongoing construction—was surrounded by unattractive views (barrier A3 and barrier A4) with heavy

Table 5
Classification of participant's physiological responses into (1) non-stress and stress; and (2) low-stress and high-stress samples based on Ensemble bagged tree algorithm.

Participant ID	Total sample	Detected stress and non-stress samples		Detected low and high-stress samples	
		Non-stress samples	Stress samples	Low-stress samples	High-stress samples
1	700	210	490	270	220
2	527	142	385	241	144
3	599	208	391	187	204
4	535	198	337	170	167
5	827	264	563	563	0
6	596	220	376	199	177
8	657	211	446	220	226
9	537	206	331	164	167
10	540	198	342	172	170

Fig. 5. Confusion matrix of the best performance Ensemble bagged tree algorithm for (a) detecting non-stress and stress samples; (b) detecting low and high-stress samples.

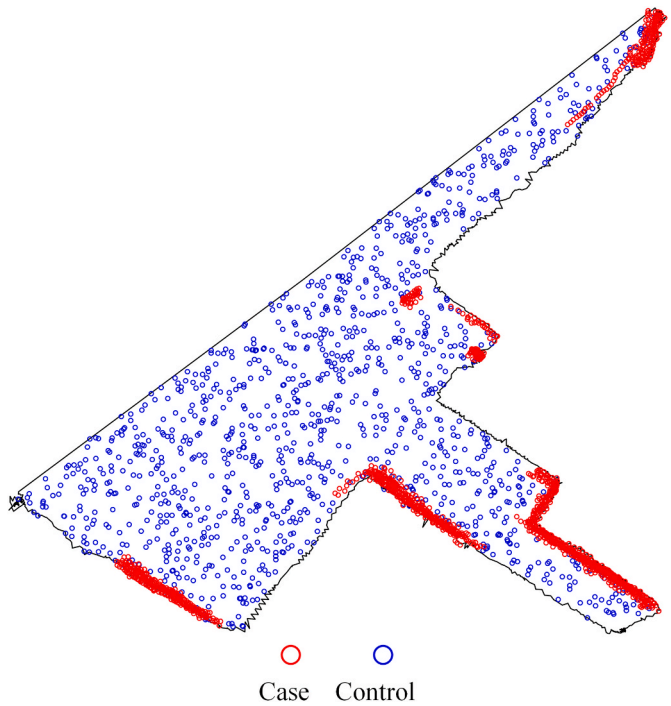


Fig. 6. The first iteration of simulated randomly generated point-level physiological data assuming complete spatial randomness. Simulated case (i.e., high-stress samples) locations are red-coloured circles, and simulated control (i.e., non-stress and low-stress samples) locations are blue-coloured circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

trucks entering or exiting the construction site (S4). Most of the participants reported feeling stressed at this spot. There were inconsistent path surface materials (F4), a dumpster and barricades (barrier F5) that obstructed the participants during the walk. There was a flower shop in segment F. The authors identified that several flower wreaths and wooden stands were obstructing the path (barrier F6 and barrier A5). The path surface was also wet (barrier F6). One participant described her interaction with this spot as: "I felt uncomfortable when I saw the funeral flower wreath on the street—It made me picture death and burial".

Risk stress hotspot 3 is located at the end of segment F. This hotspot was caused by a stair with about 11 steps (barrier F7). While some participants reported this stair to be good for their fitness, others reported feeling stressed. An increase in participants' physiological responses was observed at this spot. Lastly, risk stress hotspot 4 is located in a subway (segment H). The subway has dominant graffiti features (barrier A6), resulting in stress among the participants.

4. Discussion

In the future, cities and communities will have to be more efficient in assessing and maintaining the built environment to remain age-friendly. Sensing human physiology is one method of accomplishing this goal. This study tested the applicability of sensing human physiology for determining older pedestrians' stressful interaction with the built environment in a real-world setting using non-invasive wearable sensors. In particular, the authors deployed machine learning intelligence to detect moments of stress in older adults' physiological signals, location and environmental data collected while they were interacting with the built environment.

Several machine learning algorithms were trained using supervised and unsupervised learning methods. The results showed that the Ensemble bagged tree algorithm achieved the highest performance among other tested algorithms. Accuracy on the held-out test data (i.e., the proportion of collected samples in which the algorithm prediction matches the true label) provides an estimation of the stress detection result to be expected on a new data; therefore, the Ensemble bagged tree algorithm would be able to detect older pedestrians' stressful moments with an accuracy of 98.13% (for detecting stress and non-stress samples) and 98.25% (for detecting low and high-stress samples). The high performance of the Ensemble bagged tree algorithm is possible because it combines several decision trees (bootstrap aggregation) to produce better predictive performance; this approach helps to reduce the variance of a model [108]. The high performance of the ensemble method means that it can be used for data collected in an ambulatory, real-world setting. Ambulatory, real-world sensing of human physiology pose several methodological challenges such as missing and noisy data. For instance, if a modality is missing data for a given pedestrian or on a sample day, the ensemble method is able to abstain that classifier in order to achieve better performance.

This sensing approach has several potential applications in cities and communities. For example, urban planners and municipal decision-makers can use this approach to detect stressful locations in the environment, prioritise the high-stress locations and allocate resources to improve neighbourhood walkability. The effectiveness of the intervention can be monitored by observing how the stress levels change over

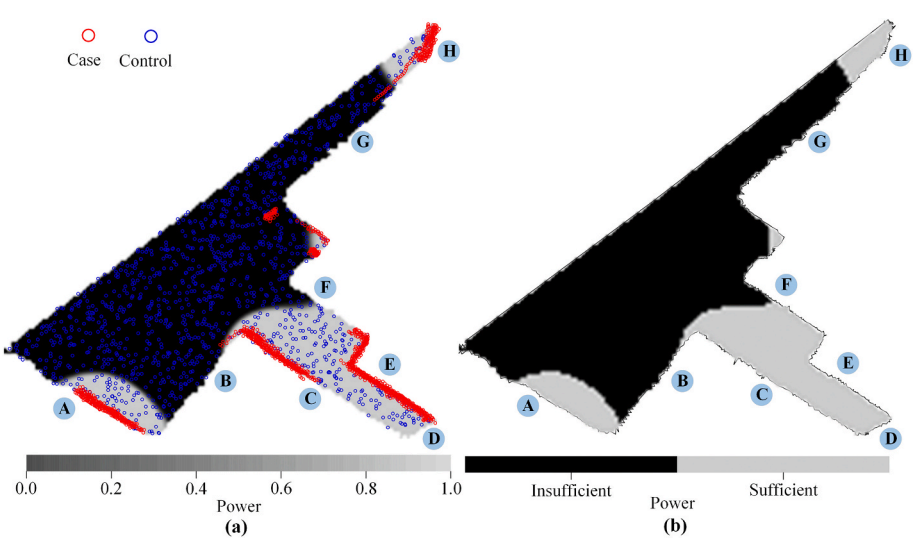


Fig. 7. Clusters of SRR high-stress hotspots within the study area (i.e., path segment A to H). (a) The proportion of simulation significant SRR high-stress hotspot clusters for the simulated 10,000 iterations. (b) Areas within the study area that are sufficiently powered to detect spatial clustering of a high-stress hotspot. Simulated case (i.e., high-stress samples) locations are red-coloured circles, and simulated control (i.e., non-stress and low-stress samples) locations are blue-coloured circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Fig. 8. Environmental barriers at locations of risk stress hotspot. Base map and data copyrighted 2020 Esri, OpenStreetMap contributors and the GIS user community.

time. Streets in cities and communities can be labelled based on the stress level to minimise encounters with environmental conditions that exceed older pedestrians' functional ability. The physiological sensing approach is user-centred, thus leading to interventions that meet pedestrians' needs. Urban design guidelines can be revised based on the physiological sensing approach. This approach is time and cost-effective because physiological signals can be collected continuously, resulting in a near real-time built environment assessment. Digital twin cities and communities can potentially incorporate the physiological sensing approach into their models to improve the planning and management of healthy, age-friendly cities and communities.

Although the Ensemble bagged tree algorithm performed better than the deep learning algorithm, the Ensemble bagged tree algorithm required sufficient labelled data for training while the deep learning required little or no labelled data. Collecting sufficient labelled data from pedestrians in cities and communities is somewhat impractical and may hinder a large-scale deployment of the stress detection algorithm in smart age-friendly cities. Furthermore, supervised learning required careful engineering and considerable domain expertise to extract and select handcrafted features that are important for discrimination. This implies that failure to extract and select the important features may affect the performance of the supervised learning algorithm. However, the deep learning algorithm automatically learns good features and produces representations that are selective to the relevant aspect of signal pattern important for discrimination. Going forward, using an unsupervised deep learning approach is imperative for the efficient deployment of the stress detection algorithm in cities and communities. To encompass this, a future study will be conducted to improve the performance of the deep learning algorithm. The authors hypothesise that developing a deep learning algorithm that accounts for interindividual variability can improve the detection of stressful interactions for pedestrians. The authors intend to deploy a multi-task learning technique to train a personalised machine learning model tailored specifically for each pedestrian but still learn from all available data.

Given that the built environment infrastructure in many cities and communities are approaching their design life, sampling peoples' physiological interactions for the entire built environment is currently impossible. The simulation-based approach adopted in this study shows promising results in generating reproducible physiological point-level data to reflect an entire study area. Detecting risk hotspot locations with high statistical power will be useful for researchers and urban planners to detect real urban stress hotspots that pose a higher risk to older adults and understand the association between built environment and stress. While identifying these high-risk stress hotspots is essential, it is only the first step to creating an AFCC. How the identified environmental barriers are addressed is critical to improving the well-being and

Fig. 9. Pictures of environmental barriers at locations of risk stress hotspot. Photographs by authors.

participation of older adults in outdoor activities. Table 6 presents a few recommendations based on the WHO AFCC guide [2] to address the identified environmental barriers in this study. Although these recommendations can be adapted and adopted in other cities and communities, it not a gold standard.

It is important to mention that the stress hotspots were identified through older adults-centred approach; this is motivated by the fact that involving older adults is very important in evaluating the age-friendliness of the environment [2,11]. Therefore, urban planners should adopt a bottom-up approach—with a supportive top-down back-up—throughout the process of addressing these stress hotspots; in this way, older adults become place-makers. As with many inclusive features, identifying older adults' stress hotspots and adopting age-friendly initiatives to address these stress hotspots could be advantageous for all generations. If a street is 'friendly' to older adults, it is likely to be 'friendly' to everyone. For example, a street that older adults

Table 6
Age-friendly recommendations to address environmental barriers.

Domain	Environmental barrier	[2] Age-friendly guide
Functionality	- Path condition (wet and slippery streets)	- Well-maintained paths with smooth, level, and non-slip surface
	- Path slope	- The path width should be sufficient to accommodate wheelchairs
	- Path obstruction	- The path should have dropped curbs that taper off to be level with the road
	- Major barriers (roadwork, steep staircases)	- The path should be free from obstructions such as street vendors, parked cars, trees, dog droppings, snow
	- Minor barriers (cracks, holes, bumps, parking meters)	- Pedestrians have priority of use
	- Street crowd	
	- Motor vehicles parked on footpath	
	- Hawkers and shops on streets	
	- Path width	
	- Path material	
	- Curb cut features	
	- Permeability	
Safety	- Pedestrian crossing	- Roads should have a non-slip, regularly spaced pedestrian crossing
	- Traffic load	- Roads should have well-designed and appropriately placed physical structures, such as traffic islands, overpasses, or underpasses, to assist pedestrians in crossing busy roads
	- Traffic calming devices	- Pedestrian crossing lights should allow sufficient time for older adults to cross the road
	- Streetlight	- Pedestrian crossing lights should have visual and audio signals
	- Directional sign	- Strict enforcement of traffic rules and regulations
	- Presence of people	- Drivers should give way to pedestrians
	- Signs of crime/disorder	- Good street lighting and visible directional sign
	- Stray dogs/other animals	- Police patrols to ensure safety
		- Enforcement of by-laws, support for community and personal safety initiatives
Aesthetics	- Views	- Regular cleaning of city and community
	- Building attractiveness	- Enforce regulations to limit noise levels and unpleasant odours
	- Attractive natural sights	- Well-maintained and safe green spaces with easily accessed seating, shelter, and toilet
	- Streetscape	- Graffiti removal
	- Litter	
	- Graffiti	
	- Pollution (noise and air)	
	- Greenery	
Destination	- Transport-related	- Available and well-maintained outdoor seating spaced at regular intervals and patrolled to ensure safe access by all
	- Public open space	- Services are easily accessed and located near older adults
	- Recreational	- Special customer service arrangement for older adults
	- Government/public services	
	- Public facilities	
	- Commercial destinations	

find easy to use might be more walkable for someone carrying luggage or a parent with a toddler in a stroller.

The authors acknowledge that some of the limitations of this research are the relatively small number of older participants, the unequal number of male and female participants and the limited physiological sensing per participant. Gender differences can influence human responses to environmental conditions, therefore the findings should be interpreted bearing in mind that the experiment was dominated by women. With data from more older participants and longer sensing periods, it may be possible to develop high-performance and personalised stress detection models. For the purpose of this study, it was necessary to have pedestrians interact with the same walking path for a more direct comparison. Although restricting participants to a specific path could affect their interaction with the environment, it was an essential step before deploying this physiological sensing approach on a large scale. In the second stage of this study, data will be collected in a free-form environment where participants will not be restricted to any particular path.

5. Conclusions

This paper presented a smart and more efficient approach to detecting older adults' stressful environmental hotspots that may restrict their mobility in the built environment. Towards this goal, wrist-worn wearable physiological sensors were employed to continuously monitor older adults' interactions with the built environment. This study adopts a multimodal information fusion technique (specifically, feature level fusion of EDA signal, PPG signal, location and environmental data using parametric or non-parametric machine learning algorithms) to minimise the effects of incorrect data acquisition and provide complementary data during human-environment interactions in ambulatory, real-world settings. The spatial relative risk function was adapted to detect stress hotspots that pose a higher risk to older adults. Several machine learning algorithms, including Gaussian SVM, Ensemble bagged tree and DBN, were trained to detect older adults' stressful interactions from their physiological signals, location and environmental data. Based on three statistical performance evaluation indicators, the results produced by the machine learning algorithms were evaluated. The obtained results show that the machine learning algorithms can achieve satisfactory performance in detecting older adults' stressful interactions (over 70% accuracy), with Ensemble bagged tree achieving the best performance (98.25% accuracy). The detected stressful interactions were spatially matched with GPS data. A simulation-based risk hotspot analysis was used to identify environmental barriers within the study area that pose a high risk to older adults. The results demonstrate that urban planners and municipal decision-makers can use this approach to more efficiently detect and alleviate stressful environmental features; as a result, improving older adults' mobility in the built environment. With more advancements in wearable sensors and machine learning intelligence to come, this work is paving the way towards assessing and improving neighbourhood environments in smart AFCC, where machine intelligence can help urban planners and policymakers make data-driven decisions.

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CRediT authorship contribution statement

Alex Torku: Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Albert P.C. Chan:** Writing – review & editing,

Supervision, Funding acquisition. **Esther H.K. Yung:** Writing – review & editing, Supervision. **JoonOh Seo:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2022.109533.

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