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The Feasibility of Integrating Wearable Cameras and Health Trackers for Measuring Personal Exposure to Urban Features:
A Pilot Study in Roskilde, Denmark

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ABSTRACT

Built environment factors such as greenery, walkability, and crowd density are related to physical activity and mental health. New emerging wearable sensors provide an opportunity to objectively monitor human exposure to street-level urban features. However, very few studies have demonstrated how to objectively measure the association between the built environment, human emotions, and health. This pilot study proposes a new approach that employs a FrontRow wearable lifestyle camera, a GPS tracker, and an Empatica 4 wristband as a sensor package to track individuals during their everyday activities. Machine-learning methods are adopted to extract urban features. For this study, volunteers were asked to conduct a self-led city tour in Roskilde, Denmark, while using the wearable sensors. Study results demonstrate the feasibility of the proposed approach and the potential for using integrated, multi-sourced data in the study of urban health.

KEYWORDS

Digital-Self, Health Tracker, Image Detection, Urban Emotion, Wearable Camera

INTRODUCTION

The ever-growing development of sensor technology offers new opportunities to understand Environmental Stress Theory (Lazarus and Cohen, 1977). Through employing personalised environmental monitors, researchers have been able to measure individuals' exposures to various kinds of environmental stressors: noise (Ueberham and Schlink, 2018), temperature (Ojha et al., 2019), light (Kanjo et al., 2018), air pollutants (Donaire-Gonzalez et al., 2019), wind and solar radiation (Shimazaki and Katsuta, 2019). The stressors in the current literature focus more on the

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physical environment, but little is known about the health effects of the built environment (Benita and Tunçer, 2019). However, built environment factors are thought to be closely related to physical activity and mental health; examples of such factors are greenery (Gubbels et al., 2016), walkability (Van Cauwenberg et al., 2016) and crowd density (Engelniederhammer et al., 2019). However, previous studies have not demonstrated how to objectively measure the association between the built environment and human emotions and health.

To assess the impact of the built environment on health, a priority is to measure the influence of street-level urban features. Previous studies have researched specific urban features. For example, urban trees that can provide shade (Nasution and Zahrah, 2014, Wolf et al., 2020) and sitting facilities that can encourage people to stay in public space (Gehl, 2013). Aside from that, other studies on the built environment have emphasised the quality of the built environment and type of amenities as important contributors to health promotion, investigating features such as walking paths, the presence or absence of nearby water and trees, lawns, birdlife, lighting, benches, facilities, playgrounds, and the type of surrounding roads and traffic (Holman et al.,1996; Giles-Corti et al., 2005).

Urban imagery is a widely used tool to represent the characteristics of the built environment. The history of using imagery in this context can be tracked to the last century (Lynch, 1960; Whyte, 1980), with Ewing and Handy (2009) being the first to utilise quantitative analysis of imagery, adopting video clips of streetscapes to measure urban design qualities (e.g., enclosure, human scale, and complexity). Furthermore, Thwaites et al. (2005) summarised urban features (e.g., sky exposure, façade continuity, visual complexity) from sequential photographs of streets taken at 25-metre intervals, laying a foundation for contemporary research on urban characteristics/qualities.

Recently, street imagery from Google Street View (GSV) enabled the consistent objective measuring of urban features on a city-scale (Li et al., 2015, Yin and Wang, 2016), and is becoming an effective tool to assess the built environment (Anguelov et al., 2010, Goel et al., 2018, Helbich et al., 2019). For example, previous studies have employed GSV to investigate pedestrian-level greenery (Hua et al., 2022), traffic safety (Cai et al., 2022), and sky and building view factors (Gong et al., 2018). GSV merits attention in the research on health and the built environment (Rzotkiewicz et al., 2018), but—with regard to health studies—some argue it still cannot take the place of in-person observations due to inconsistencies and inadequate resolution (Clews et al., 2016). Both researchers from the domains of public health and urban planning advocate for the personal level measurement of human responses to urban metrics (Bell et al., 2014, Chrisinger and King, 2018). As a solution to this issue, novel methods, such as tracking individuals by personalised sensors in urban environments needed to be explored.

With the advance in technology, the emergence of the wearable camera has enhanced researchers' ability to capture in-person images from footpaths rather than cars' views from streets. A wearable camera can be worn front-facing and can automatically take front view photos or videos. These images do not only represent the urban environment, but also form a digital record of personal exposure to urban features, such as greenery (Zhang et al., 2021), food store and dieting habits (McKerchar et al., 2020), residential neighbourhoods and children's activities (Chambers et al., 2017), and water space and children's recreation (Pearson et al., 2017). Thus, wearable cameras provide an opportunity for high-resolution measurements of urban features at the individual level.

At the same time, body-worn health trackers are utilised increasingly to record the physiological signs in human daily life, such as the Zephyr BioHarness[1] (Laeremans et al., 2018), Emotiv EPOC[2] (Aspinall et al., 2015), Empatica 4[3] (Benita and Tunçer, 2019), and the Microsoft Band 2[4] (Birenboim et al., 2019). Taking advantage of these sensors, blood pressure (BP), heart rate (HR), and heart rate variability (HRV) are broadly used to indicate physical health conditions in the urban environment, while accelerometers are regarded as physical activity (PA) monitors, examining the speed, direction, and acceleration of movement (Burgi et al., 2015).

As for monitoring individuals' emotional responses to the environment, electrodermal activity (EDA) is a physiological measure used for emotion recognition (Yu and Sun, 2020). EDA, measured at the skin's surface, will rise if the skin receives signals from the brain (Yu and Sun, 2020), so wristbands with an EDA monitor are widely used to assess human emotional arousal to environmental stressors (Kushki et al., 2011), such as noise (Benita and Tunçer, 2019), ultraviolet radiation (Kanjo et al., 2018) and the built environment (Chrisinger and King, 2018).

Similarly, electroencephalography (EEG) is another physiological evaluation of emotional activity. Researchers have used electroencephalography (EEG) technology to assess urban experience and humans' psychological state (Aspinall et al., 2015, Mavros et al., 2016). However, current studies employing wireless EEG headsets often control the duration of wearing to a short period, for example, a 25-minute walk in Aspinall et al. (2015) experiment and a complete 16-minute task in Lin et al. (2020) study. It is possible that the short duration experiments were because of participants' limit to the acceptability and comfort of wearing the headset in the urban environment. Compared with a mobile EEG headset, some wristbands and EDA data are more often employed for long-time tracking of humans' emotional responses in daily life (Bolliger et al., 2020).

The latest research is gradually integrating multiple personalised sensors as a package to measure people's physical and mental health (i.e., stress) in urban environments (Ojha et al., 2019, Runkle et al., 2019). Some studies also have explored the possibility of integrating cameras and health trackers (Resch et al., 2020, Rybarczyk et al., 2020). However, since the value of in-person imagery has not been explored thoroughly, the integration of wearable cameras and health trackers in research is still limited—especially on how to extract image features and fuse image data with other source data to analyse patterns of human-environment interactions.

To overcome current limitations, this study proposes a new approach to assessing personal exposure to urban features and human emotional responses by combining cameras and health trackers, then applying this approach in a pilot study to test the feasibility. The authors' aim to automatically detect urban features from imagery by machine learning methods and use EDA data to indicate humans' emotional responses. Specifically, the study seeks to:

- Explore the workflow of integrating wearable cameras, GPS, and health trackers as a sensor package to track individuals in the urban environment.
- Provide a technical route of fusing data from sensors to quantify personal exposure to urban features (e.g. greenery, water, overcrowding, traffic) and emotional responses.
- Examine the feasibility of a multi-sensor approach and discuss the key factors crucial to the application's success in practice.

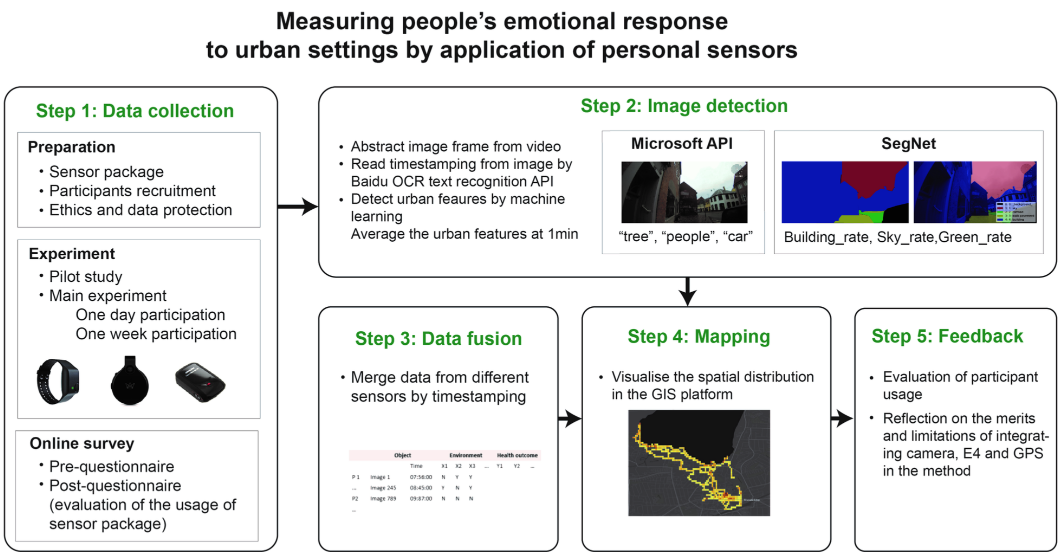
METHODOLOGY

This study focuses on physical activities taking place in a public city environment rather than a private space. As participants are acting as different "channels" to link up body responses with urban features, this research involves no experimental procedures, medical research, or behavioural manipulations, only device-based measurements of people's exposure to the urban environment. The authors utilised a naturalistic data collection strategy in an uncontrolled setting, similar to that reported by Rybarczyk et al. (2020) to test the possibility and feasibility of integrating GPS, wearable cameras, and health trackers in the urban environment. This study will follow the methodology framework shown in Figure 1 and add new evidence to the growing applications of multiple sensors in urban studies.

INSTRUMENTS

Each participant was provided with three devices: a wearable camera, a GPS, and a health tracker. Four brands of wearable cameras were considered during the experiment design phase: Narrative Clip[5], GoPro[6], iON Snapcam[7] and FrontRow[8]. Narrative Clip was chosen as it was found to be a

Figure 1. Methodology framework



light and simple device for users to wear in daily life over a long period of time (Zhou et al., 2019, Zhang et al., 2021). GoPro had been used in a few other studies (Rybarczyk et al., 2020), but the authors did not choose GoPro because it could not be worn directly on clothing and was more expensive. Furthermore, the authors tested the function of iON Snapcam and FrontRow (FR) and found that FR had longer battery life, which made it more reliable than iON during long-time standby. Also, FrontRow had been selected in several other studies after comparison with other camera brands (Mair and Shackleton, 2021, Gao et al., 2020, Chen et al., 2021) since it could capture imagery clearly and easily. The FR camera also featured a touchscreen and a media button to start/pause/stop, making it more user-friendly. Additionally, the "story" mode of FR supported 5, 10, 15, and 30-minutes interval time-lapse shooting, and the images would be compressed and stored as a short video. After considering the availability, cost, and function, the authors decided to use the FR camera (Table 1).

To track individuals' physiological responses, the medical-grade device Empatica 4 (E4), worn on the wrist of the non-dominant hand, was utilised. E4 is equipped with an electrodermal activity (EDA) sensor, a photoplethysmograph (PPG) sensor and a 3-axis accelerometer sensor, enabling real-time measurement of sympathetic nervous system activity and other physiological responses. Previous studies have successfully used the EDA from E4 to assess human stress levels in the urban environment (Benita and Tunçer, 2019, Kyriakou and Resch, 2019). As shown in Table 1, the parameters included: 1). accelerometer (ACC); 2). EDA with a sampling rate of fs = 4 Hz (i.e. four readings per second); 3). inter beat intervals (IBI): intermittent output with fs = 64 Hz; 4). blood volume pulse (BVP) with fs = 64 Hz; 5). skin temperature (SKT): data from temperature sensors (°C); 6). heart rate (HR): from IBI and computed in spans of 10 seconds.

The data from the FR and E4 devices were coupled with the location data from the GPS device (Qstarz BT1000XT[9]). This device is similar in size and weight to a small cell phone (7.2 cm x 4.7 cm x 2 cm) and collects the GPS position every five seconds. This GPS tracker had been tested in previous studies (El Aarbaoui and Chaix, 2020, Batista Ferrer et al., 2018) to effectively track people's movements in the urban environment. Figure 2 shows the data sample and technical indexes from sensors.

Table 1. Technical specifications of sensors

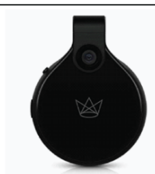
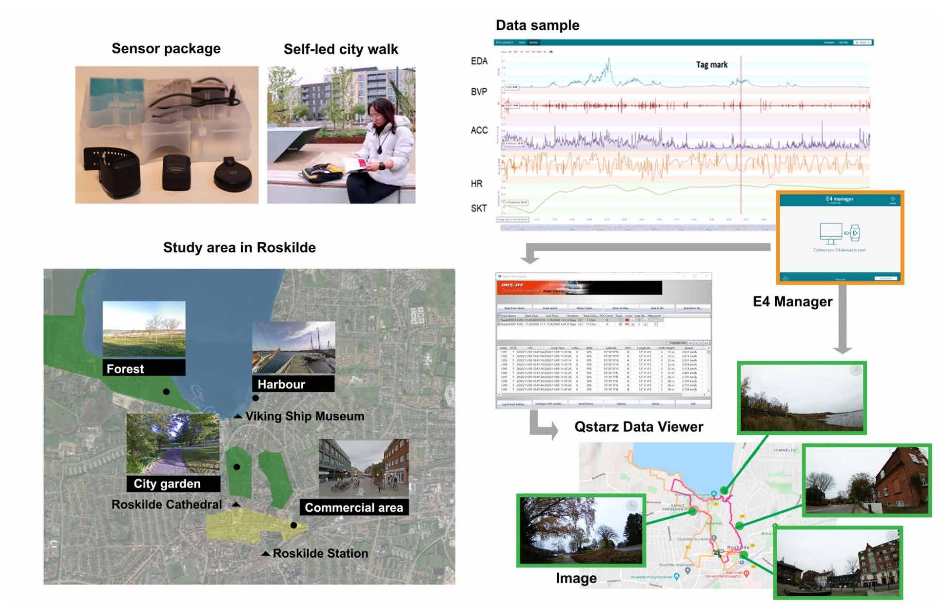
Empatica 4 (E4)		
	Price	$1,690.00
	Function	PPG Sensor: measures blood volume pulse (BVP), from which heart rate variability can be derived.
		EDA Sensor: measures the changes in certain electrical properties of the skin.
		3-axis Accelerometer (ACC): records motion-based activity.
		Infrared Thermopile: reads peripheral skin temperature (SKT).
		Event Mark Button: tags events and link them to physiological signals.
	Size	Case is 44 x 40 x 16 mm; Wristband is 110 –190 mm.
	Battery	20+ Hours Streaming Mode; 36+ Hours Memory Mode
	Weight	25 grams
FrontRow (FR)		
	Price	$399.00
	Function	Image
		Video
		Time-lapse shooting mode
	Resolution	2688 x 1512 max
	Battery	Up to 10 Hours
	Camera	Main lens is 8MP and F2.2; Rear lens is 5MP and F2.0
	Storage	32GB (RAM 2GB)
	Weight	59 grams
GPS device		
	Price	$115.96
	Function	Records latitude and longitude coordinates and UTC time.
	Model	Qstarz BT1000XT model
	Size	72.2 (L) x 46.5 (W) x 20 (H) mm
	Battery	45 Hours
	Weight	64.7 grams

Figure 2. Sensor package and data example



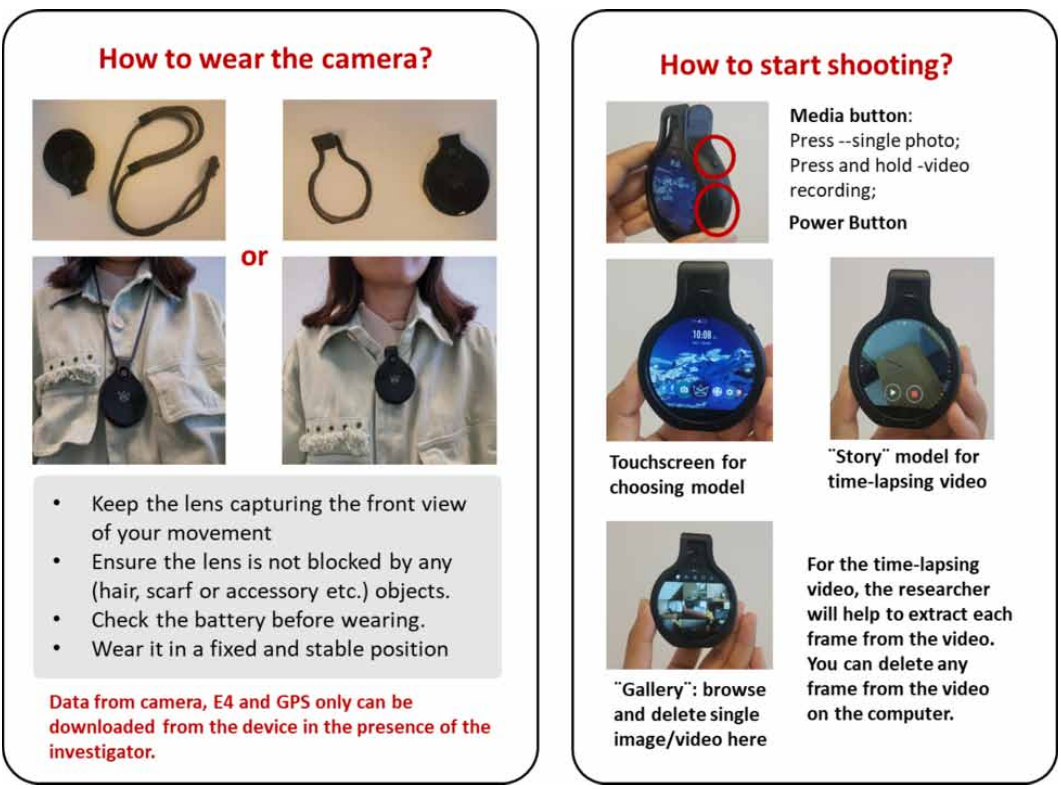
PROCEDURES

The study was approved by Aarhus University's Research Ethics Committee (IRB) and complies with the General Data Protection Regulation (GDPR legislation, October 9, 2020) in order to protect individual's data. The letter of information and consent form used in this study can be found on the project website. People had to sign the consent form but were informed that they were free to exit the study at any time. The purpose of the study and the process of data collection were explained to all participants. The data collection was completely anonymised containing no self-identifying information. The research team made an online video tutorial to lead and train participants before implementation.

The importance of protecting the confidentiality of participants and third parties while using wearable cameras had been emphasised in the work of Kelly et al. (2013). To help participants understand how and when to deactivate the camera, the authors explained the ethical issues to participants both verbally and in the written consent form. Participants were also provided with a reference card, similar to that used in previous work by Gelonch et al. (2019), containing instructions on all the procedures that participants needed to know and explaining the camera to other people who may incidentally appear in the low-resolution images (Figure 3). A three-stage procedure was completed by participants in the data collection process after consenting to the study and finishing the sensor-use training:

1. **Pre-survey:** Before starting walking, participants had to finish a pre-survey, including providing demographic information, self-assessments of mental health, and general baseline satisfaction about the quality of the built environment in the city. The authors built this electronic survey

Figure 3. Reference card of how to use the camera



based on the survey tool, Survey Monkey[10] and provided participants 10 minutes to finish the survey on the tablet after meeting on site.

2. **Objective measurement during the self-led city tour:** This study was conducted in a natural setting with two options: 1). One-day participation, where participants were asked to wear sensors to conduct a self-led city tour around the study site and were allowed to walk/sit/cycle/take a bus while wearing the sensors; b). One-week participation, where participants were free to wear the sensors during their real-life activities in the urban environment.
3. **Post-survey:** After returning the device to the project investigator, participants were invited to complete a post-survey. This was a short questionnaire referred to as the Wearable Smart Device Questionnaire designed by Puri (2017) on the usability of sensors and problems encountered. The objective of the post-survey was to investigate participants' feelings, experiences, and expectations about wearing multiple personalised sensors. The post-survey was also built based on Survey Monkey. However, in most situations, it became dark (close to 3 pm) after completing the walk, so the authors sent the link for the post-survey to participants by email.

The purpose of the pilot study was to assess the feasibility of the authors' approach in a fieldwork setting. Thus, the main focus was on the objective measurement and feedback from participants. The rest of the paper will highlight the results obtained from the pilot study and will also discuss limitations.

PARTICIPANTS

For this pilot study, 12 volunteers were recruited to conduct a self-led city tour around the centre of Roskilde, Denmark, while using the wearable sensors in order to objectively measure the association between the built environment, human emotions, and health. The city of Roskilde is located in north-central Zealand and is the 10th largest city in Denmark. This study site was located in the central town of Roskilde and included the main public spaces: the biggest commercial street, Roskilde Harbour, Roskilde Cathedral, the Viking Museum, and the nearby forest. The data collection was conducted in November 2020, and the average temperature during the fieldwork was five degrees Centigrade.

The authors managed to recruit 12 participants (five female and seven male) from the university for a one-day participation. Their participation was voluntary and unrewarded. Four of the participants were Danish and the others were immigrants from Africa, Asia, and Europe. To test the feasibility, the authors selected participants from different age groups: three participants were ages 20-30, four participants were ages 30-40, three participants were ages 40-55, and two participants were over 55 years of age. The average duration wearing a sensor was 2 hours, 30 minutes, and the longest duration was 4 hours.

Of the participants, 10 completed the 3-stage procedure, including the pre-survey, camera experiment, and post-survey. One participant forgot to turn on the GPS tracker, and three participants had problems while using the FR camera. Participant number 3 put the camera inside her jacket and used the wrong mode. Participant number 5 wore a scarf that blocked the camera slightly. Participant number 8 forgot to start the recording. Therefore, in the data analysis, the authors selected valid data from five participants (mainly walking alone) as shown in Table 2.

The initial plan of this study was to test the feasibility in one-day and a one-week period for comparative purposes. The authors asked participants whether they would like to participate for one-day, and then later participate in the one-week study, so the one-day sample was the same sample recruited for the one-week study. Finally, considering that the data collection period (close to winter) may have deterred some participants from opting for one week, two participants (5 and 7) agreed to join the one-week participation and wore the sensor package in their outdoor activities (walking/cycling/taking a bus/running). However, since Participant 7 did not synchronise the camera time before wearing it, the image data could not be matched with other data by timestamp. Therefore, the authors only analysed data from Participant 5, who wore the sensors from November 16th to the 23rd, 2020.

Table 2. Participants and participation

Date	No	Gender	Age	GPS	E4	FR	Pre-Survey	Post-Survey	Main Activity	Duration	Alone or With Others
07/11	1	M	30-40	Valid	Valid	Valid	Yes	Yes	Walk	3h/27min	Alone
	2	M	40-55	Valid	Valid	Valid	Yes	Yes	Walk/Cycle (Morning)	3h/35min	Alone
									Walk (Afternoon)	1h/16min	Not Alone
08/11	3	F	20-30	Valid	Valid	No Image	Yes	Yes	Walk	4h/16min	Not Alone
	4	M	20-30	Valid	Valid	Valid	Yes	Yes	Walk	2h/33min	Alone
09/11	5	F	20-30	Valid	Valid	Blocked Slightly	Yes	Yes	Walk	0h/28min	Alone
	6 (D)	M	40-55	Valid	Valid	Valid	Yes	Yes	Walk	3h/29min	Alone
11/11	7	M	30-40	No Data	Valid	Valid	Yes	Yes	Walk	0h/47min	Alone
13/11	8	F	30-40	Valid	Valid	No Image	No	No	Walk	2h/19min	Alone
21/11	9	M	30-40	Valid	Valid	Valid	No	No	Cycle	0h/33min	Alone
26/11	10 (D)	M	>55	Valid	Valid	Valid	Yes	Yes	Walk	1h/51min	Not Alone
	11 (D)	F	40-55	Valid	Valid	Valid	Yes	Yes	Walk	2h/18min	Not Alone
27/11	12 (D)	F	>55	Valid	Valid	Valid	Yes	Yes	Walk	2h/17min	Alone

DATA TREATMENT AND ANALYSIS

Image Detection

The images were collected by the participants via the FR camera. Since the authors did not provide an Internet connection for the FR, it was necessary to calibrate the time with the phone every time before wearing the camera, then starting the time-lapsing mode ("story" mode) to record the view in front of participants continually. All images from the "story" mode were automatically compressed into a video and saved in the camera at the end of wearing.

To deal with the images, first, the authors used a professional video player (KMP player) to extract every image frame from the compressed video; next, they used the Baidu OCR text recognition API to read the timestamp from the clock on the top-right corner of the image (Figure 4a) to build the time sequence. Although FR cameras can take an image every 5 seconds, the timestamp on each image only includes time in hours and minutes. Therefore, the authors aggregated all the indices from imagery in the following analysis by calculating the average value within one-minute intervals (Figure 5).

Microsoft Cognitive Service (MCS) is a product from Microsoft that provides access to machine learning algorithms for detecting pictures. By using the MCS API, the authors could detect the urban features by identifying the existence of "tags" (Figure 4b). In the MCS analysis, the authors detected the urban settings and labelled five categories of urban features, as shown in Table 3. Every category, regardless of the number of tags, was classified according to the binary one (1) ("existing") or 0 ("non-existing"), as in the approach reported by Zhang et al. (2021).

The authors adopted another model, SegNet, to outline the sky, greenery, and buildings in an image. Although MCS could identify the existence of specific urban features, it could not report the number/size of each tag to classify the exposure into "Low," "Moderate," and "High" levels, which was important for longitudinal measurements. Thus, taking greenery as an example, the authors could evaluate the intensity of greenness over the daily exposure.

Table 3. Tags related to urban features

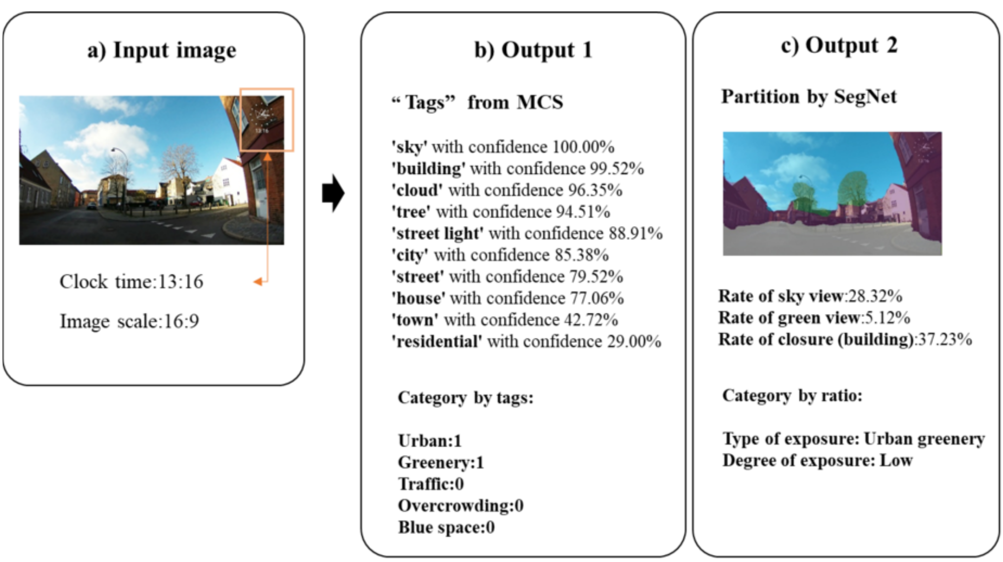
Urban Features	Tags Detected From MSC
Greenery	"tree" or "grass" or "forest" or "plant" or "bushes"
Water	"lake" or "water" or "sea" or "ocean" or "pond"
Overcrowding	"people" or "person" or "human"
Motor Traffic	"car" or "vehicles"
Non-Motor Traffic	"bike" or "bicycle"

SegNet is a segmentation model with a deep, fully convolutional neural network architecture that can partition any image into defined categories (Badrinarayanan et al., 2017). Compared with other segmentation tools (e.g., DeepLab-LargeFOV, FCN, DeconvNet), SegNet shows a superior ability in smooth segmentation (Badrinarayanan et al., 2017); thus, SegNet is widely used to analyse urban features in urban images.

This study trained the SegNet model based on the Keras framework (accuracy rate is 0.8122) training to detect three categories: sky, green, and building, as shown in the lower half of Figure 5. To summarise the characteristics, the authors calculated the rate of greenery to building (G/B) and classified the result into two levels. If it was <1, it meant the ratio of greenery on the image was lower than that of buildings, indicating "urban greenery"; If the rate was >2, it meant the ratio of greenery was greatly higher than that of buildings, indicating "natural greenery." The authors were also able to distinguish between "narrow space" and "expansive space" by calculating the rate of building to sky (B/S). Also evaluated was the "shadow from greenery" by calculating the rate of greenery to sky (G/S).

In all, there were two outputs based on image analysis: 1). Detecting the urban settings and measuring urban features from the one-day participation (Figure 4b); 2). Evaluating the intensity and characteristics of daily greenery exposure (Figure 4c) from the one-week participation. The results of the image analysis were linked with the GPS and physiological data through data fusion.

Figure 4. Image example: outputs from MCS and SegNet



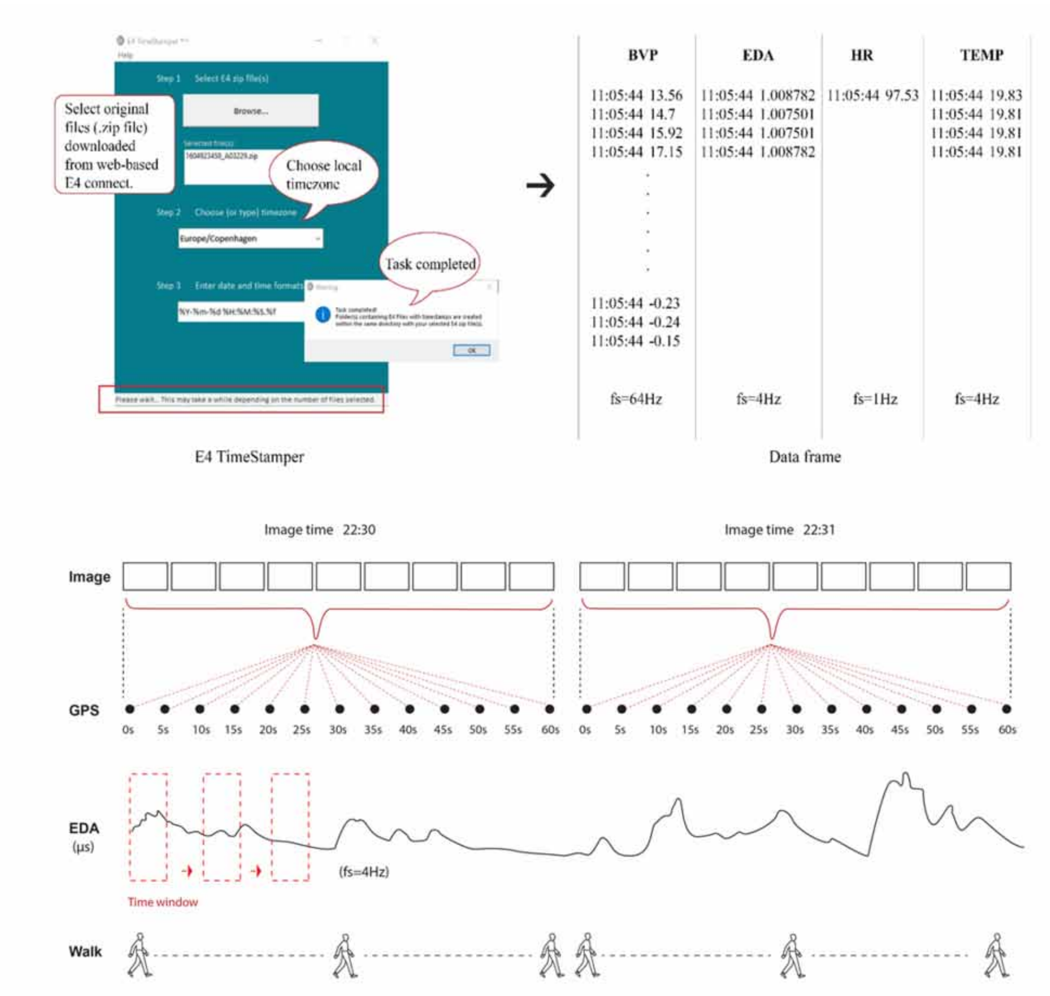
Data Fusion

Data fusion aims to link up the image data and physiological data with GPS data, in order to locate the urban features and their effects on mental health (Figure 5). In our study, the GPS tracker recorded the location every five seconds. First, based on the previous image detection, the authors assigned the average value of urban features (1-minute interval) for the 12 GPS points within the exact one-minute.

Second, the authors used EDA as an indicator of the emotional responses measured by the sensor on the E4. EDA features have been regarded as a proxy measure of stress or mental health in previous studies (Cecchi et al., 2020, Pakarinen et al., 2019, Setz et al., 2010). Before linking up EDA data with the GPS data, the authors used an open-source application E4 TimeStamper[11] (© 2020 Imran Ture), as shown in the top half of Figure 5, to automatically timestamp each physiological sample in the E4 data files, based on the local time zone (Roskilde, Denmark). Additionally, the authors cut the first and the last 60 seconds from the database for each user to avoid the irrelevant physiological responses caused by people's preparation and adjustments.

Since the EDA data was recorded every 0.25 seconds (Hz = 4), to link it with GPS data, the authors needed to reduce the frequency of the health data to every five seconds. To keep the features

Figure 5. Timestamp and data fusion



of the original EDA data, the authors extracted the average value and maximum value of EDA data within every five seconds, and merged them with the GPS data by the timestamp.

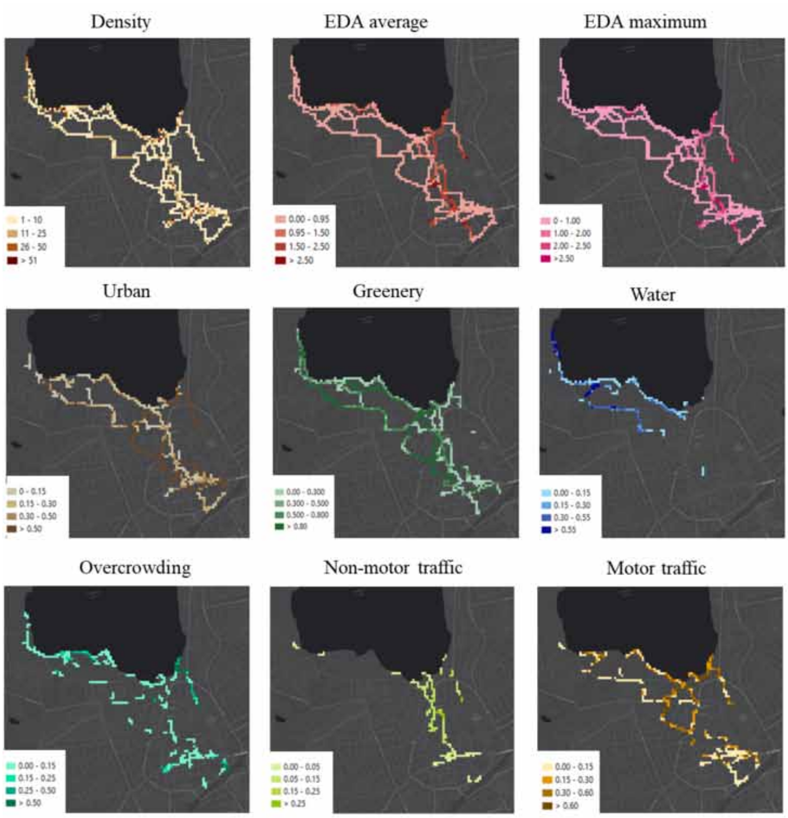
Finally, all data were linked up to form a new database with the information of location, timestamp, the average EDA, the maximum EDA, index of "urban," index of "greenery," index of "traffic," index of "overcrowding," index of "blue space," the rate of greenery, the rate of sky, and the rate of building. Afterwards, a Geographic Information System (GIS) was employed to map data aggregately through spatial interpolation and to visualise the results.

RESULTS

Urban Features and Health Effects

The authors aggregated the spatial distribution of urban features and health effects within a 30 x 30 meter grid and overlaid them with the geographical context to visualise the results (Figure 6). Overall, the highest EDA responses were located in the central city, including the station and the main street from the centre to the harbour area, where the traffic is busy. The lowest EDA responses appeared near the forest, garden, and seaside areas. In this study, the authors did not define a specific level of stress. It was known from existing studies that EDA data is associated with emotional arousal; however, one needs professional knowledge to define specific levels of emotions. Given the authors' lack of professional knowledge for defining specific levels of emotions or stress, they looked at the actual EDA scores. The mapping of EDA data indicated the potential of integrating physiological data with geographical data to spatially assess the health effects of urban features.

Figure 6. Measurement of urban features and health effects



EDA average	
Mean	0.64
Standard deviation	0.88
EDA maximum	
Mean	0.67
Standard deviation	0.93
Urban	
Mean	0.23
Standard deviation	0.34
Greenery	
Mean	0.44
Standard deviation	0.41
Water	
Mean	0.11
Standard deviation	0.26
Overcrowding	
Mean	0.07
Standard deviation	0.18
Non-motor traffic	
Mean	0.02
Standard deviation	0.06
Motor traffic	
Mean	0.10
Standard deviation	0.22

From the authors' observation of personal exposures to urban features, they found several "popular" spots with higher numbers of people, which might be preferable places for walking, such as commercial streets and the forest area near the harbour. Similarly, they found the spots with higher numbers of bikes, which might be popular cycling routes, such as the road from commercial streets to the harbour area, and parking areas with higher numbers of vehicles, such as the parking area near the Viking Ship Museum. Besides, the mapping of exposures to greenery and water represents the distribution of urban natural elements to some extent. The findings show that this pathfinding study points the way to quantify urban features at the individual level.

In the context of spatial planning, the methodology adopted in this paper provides researchers with a data-driven measurement of micro-level urban design features, such as trees, water, and birdlife in public open spaces, which is significant for urban studies (Giles-Corti et al., 2005, Whitley et al., 2005, Hoj et al., 2021, Koohsari et al., 2018, Koohsari et al., 2015). For example, incorporating green and blue spaces in urban planning may enhance mental health and improve the well-being of urban residents given the findings suggest these urban features are associated with lower EDA scores. The authors hope more urban policy makers, architects, urban planners, and designers can apply this approach to assess the association between urban features and human mental health in practice, further improving urban quality and innovating place-making strategies in public open spaces.

One-Week Exposure

Based on data collected from Participant number 5, the authors assessed the personal exposure to greenery by comparing the ratio of buildings, sky, and greenery in each image. For example, Figure 7 shows the spatial distribution and characteristics of health and green exposure during the one-week daily routine for Participant number 5. The measurements show the exposure to natural greenery during commuting (to office) with the high level of expansiveness and low level of shadow. When the exposure to greenery near living areas (home, market, and mall) is high, the overall EDA level decreases accordingly, which suggests a positive association between greenery exposure and mental health. This shows that the authors' approach has merits when it comes to long-time tracking and a high spatiotemporal coverage in a real-life situation. Although the authors cannot explore conclusive evidence from one participant's data, their method shows the possibility of suggesting "green" benefits to EDA responses from the individual perspective.

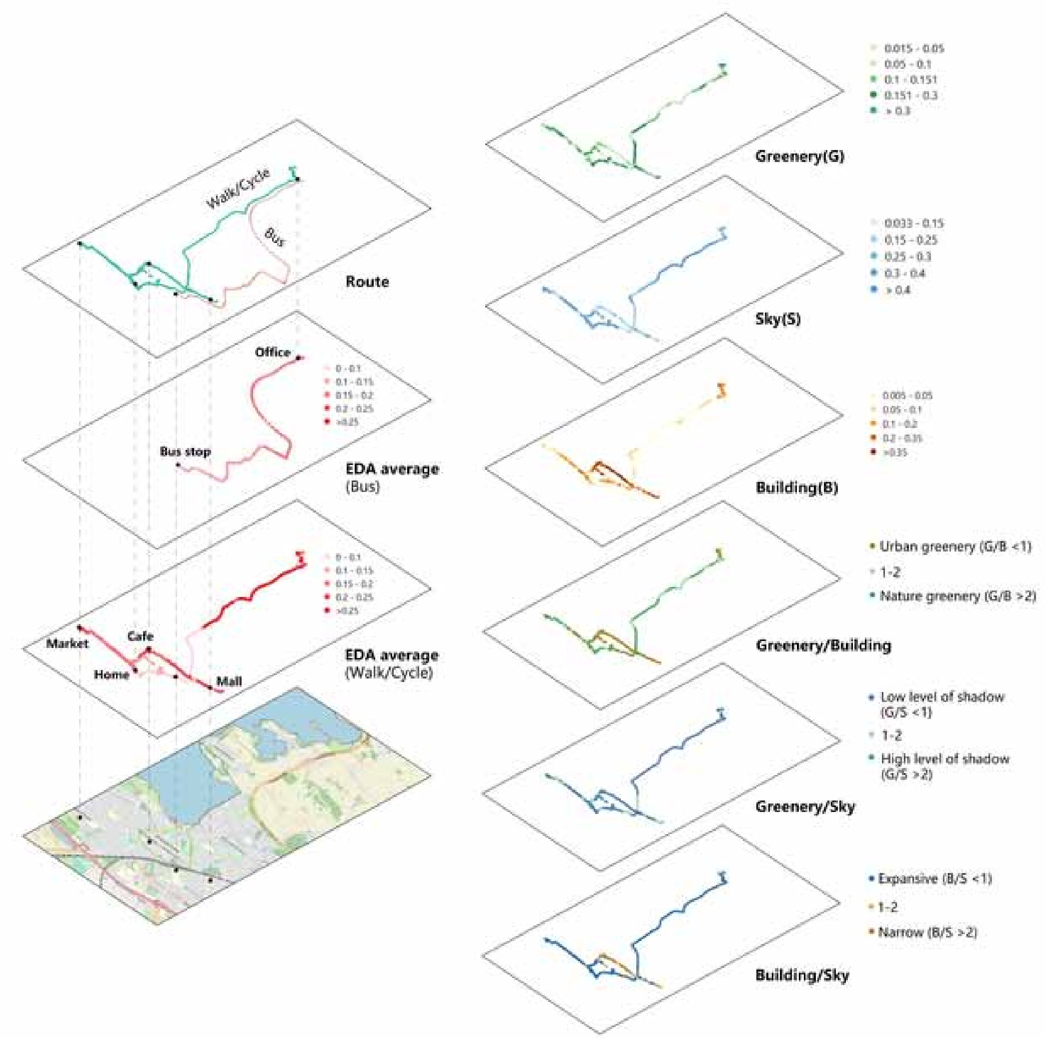
Post-Survey Feedback

Since it is the first time the FR camera and E4 wristband have been combined in a study, the authors employed a post-survey to collect participants' feedback about the sensor package. Participants answered 15 questions regarding the comfort, operation, and concerns of wearing the camera in addition to the E4. As shown in Figure 8(a), participants found the devices easy to use. They did not get complaints from others. They did not feel embarrassed to wear the sensors and did not find them stressful to wear. Over half of the participants were satisfied with the devices, but some initially felt confused about how to use them, especially the FR camera, where the recording mode can be changed or paused by incorrect use, potentially decreasing the number and quality of images at the end.

Participants also reported that they were concerned about privacy. For example, one participant said, "I need to remember to turn off the camera when I use the toilet." Also, less than half of the participants would have liked to wear the sensor package for a longer time (e.g., 24-hrs.) during daily life, and this study only recruited two participants who were willing to wear the sensor package (only in the urban environment) for one week. For longitudinal personal tracking in daily life, issues related to privacy protection, sensor management, data security, and data quality require further consideration.

These aspects aside, participants provided comments on several issues related to the usage of the devices. First, it was found that the camera is not convenient to handle during the night. Since this study was conducted in the winter and it usually becomes dark after 3:00 pm in Denmark, this was a common problem for people who walked in the afternoon. Second, there are two ways

Figure 7. One-week exposure



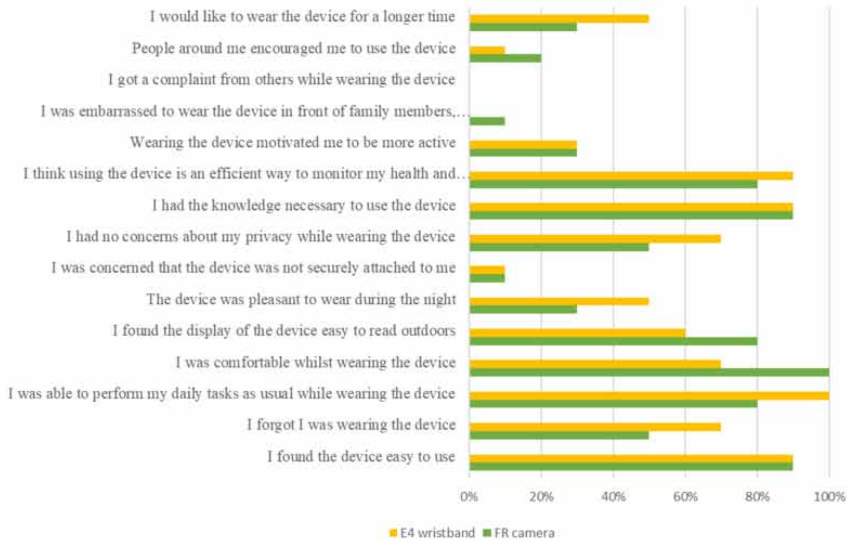
to wear the camera: string or clip (Figure 8b). The feedback indicated that the string worked better than the clip because the camera's weight could change its angle (e.g., face the ground), and the lens was easily blocked (e.g., by a scarf, hair, etc.) when clipped onto the collar. Thus, it is better to use strings to attach the camera stably by adjusting the length. Additionally, as for the E4 wristband, some reported that long-time use during daily activities could cause slight pain and leave marks on the wrist (Figure 8c).

DISCUSSION

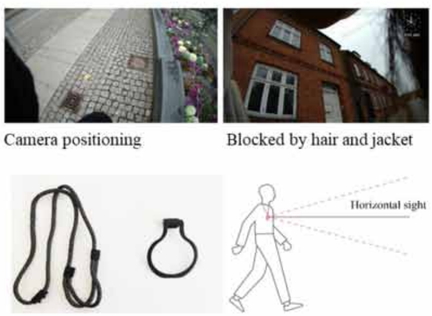
Contribution

This paper has proposed a novel approach to measuring personal exposure to urban features and its effect on health by integrating a wearable camera, GPS, and health tracker as a sensor

Figure 8. Feedback from the post-survey



a) Feedbacks from participants



b) Wear the camera

c) Mark on the skin after wearing E4 for 3h

package. The authors tested the feasibility of this approach in a pilot study and adopted a machine learning method for image analysis. Then, they successfully fused multiple-sourced, personalised data to test the feasibility of using sensors to assess the association between urban features and physiological responses. The novelty of this study is furthering the understanding of opportunities and challenges associated with the use of multiple sensors to explore the effects of urban features on mental health. To our knowledge, this study is the first to detect urban features from personal imagery via machine learning and link up urban features to body responses at the individual level.

The results proved the feasibility of integrating imagery, geo-information, and personal physiological responses, and they also demonstrated the potential of using integrated, multi-sourced data to assess personal exposure to the urban streetscape and the health effects of urban features. The participants' feedback clearly shows that the integrated sensor package was found to be user-friendly for participants in the pilot study. Lastly, the authors' hope that the approach proposed in this paper can contribute to the learning process of employing various sensors and designing data collection campaigns for urban studies.

Limitations

This paper demonstrates the feasibility of integrating three personalised sensors to achieve objective measurements at an individual level. As a pilot study, this investigation included a small number of participants, and most of them came from a single organisation. As this study used a naturalistic data collection strategy in an uncontrolled setting, and participants were free to decide their route and activity duration, this design caused our data to be a mixture of complete and less-than-complete records, leading to an unbalanced spatial-temporal distribution of GPS points in cities. For example, the authors aggregated more data from different participants in the city centre, but few in areas far from the centre. The unequal density of points may limit the value of data for spatial analysis and lead to less robust conclusions. Besides this, we only had one participant's data in the assessment of the one-week exposure, so the results could help test the feasibility of integrating sensors for longer-time tracking, but cannot be generalised to a broader population, which needs more conclusive evidence of daily exposure. Here, the authors summarise the limitations in our study that may have "biased" the results, which the authors hope to improve in subsequent studies.

First, this study was conducted in the winter. The weather and outdoor temperature may affect the body's responses. Second, irrelevant, and unexpected factors from environments, especially noise, such as party noise, cheers, music, and dog barks may affect the measurements, but were not captured or controlled for in the study. The study was conducted in a natural experiment setting; thus, participants were free to wear the sensors during their normal activities. The limitation associated with this approach is that it is not possible to measure other things affecting the individual, such as coffee, food, medicine, music, phone conversations, and meetings with friends. Lastly, incorrect handling of sensors (e.g., forgetting to start recording, inaccurate camera angle, etc.) and technical problems (e.g., GPS signal loss) may decrease the quantity and quality of data. It is vital to provide clear instructions and necessary training to participants, help them with the sensors, and check the sensors regularly whilst wearing them. To implement larger-scale studies, urban planners and researchers need to control for some of the climactic, contextual (i.e., ambient noise), interactive (i.e., operator error), and technical factors, all of which are critical for obtaining high-quality data.

It is worthwhile to make a comment regarding the ethics of the authors' approach. A reference card was used to explain ethical issues for participants prior to data collection. Although there were no complaints from members of the public who were spontaneously captured by the cameras, the authors' believe that it is essential to understand how to manage the ethical issues for future studies, if future studies are aiming to explore the science behind the association between environment and health using this approach. Especially with the widespread development of the Internet of Thing (IoT), future studies can investigate the interaction between humans and the environment through the deployment of sensors in a given built environment, which may also have the ability to connect with people's wearable sensors. In this way, the authors need more consideration of ethical issues, such as consent, privacy, protection, and risk management to regulate the reasonable use of personal data. As for the integration of various sensors, the main challenge is data fusion. Although the authors adopted machine learning to read urban information from imagery automatically, considerable efforts were still needed to link the data. The first challenge associated with this was building the timestamping for every single image. We utilised the Baidu OCR recognition API to read the timestamping from the "clock" on the right top of the image. However, there were failures in reading the timestamps if there were complicated backgrounds or other unnecessary texts in the image (e.g., shop brand names in the images).

The second challenge was unifying the frequency of data. Notwithstanding that the FR camera supports time-lapse shooting, it directly condenses imagery into a short video for storage, making it hard to obtain the image at a fixed frequency. Our images were extracted via a professional video player; however, this may not be the optimal way to extract images. Since the FR camera supports adjustment of the time-lapsing intervals from one second to 15 seconds, extracting single images at the correct frequency makes higher resolution measurements seem achievable.

Although MSC provides users access to advanced cognitive algorithms for image detection, it is essentially a black box and, thus, this paper cannot comment on which deep learning algorithms are used in MSC. This may limit the comparability with other studies concerning process images. As for the outputs from MSC, the authors suggest that future studies use statistical methods to investigate the data potential, such as categorical principal component analysis (CATPCA). As the authors have learned from this study, MSC generated various tags from imagery, so future studies can use CATPCA to reduce the dimensions of data and further output the principal components (PCs) based on the original data. Then, it would be feasible to adopt a statistical methodology to examine the association between PCs and human physiological body responses.

Lastly, as this paper does not aim to analyse empirical evidence, the authors did not precisely process EDA data and GPS data to conduct spatial analysis. Instead, they focused more on the FR camera and image detection because this is the first application of an FR camera in urban studies. As for the biological data, this study did not use the temperature data considering the weather, but previous studies have shown that stress response is not only associated with EDA increases, but also skin temperature decreases (Park et al., 2013, Picard, 2009). The authors suggest future studies include other data from the E4 wristband, for example, Kyriakou and Resch (2019) introduced a new algorithm to detect moments of stress (MOS) based on EDA data and skin temperature. The authors also suggest future studies use open-source algorithms and software, such as cvxEDA[12] and Ledalab[13] to extract the EDA features professionally (i.e. the tonic and phasic changes of EDA signal), which are useful for future studies.

CONCLUSION

This paper proposes a new approach to personal street-level tracking. In the authors' approach, they employed a wearable camera, a GPS device, and a health tracker as a package and used easily applied machine learning methods to process image data. They then fused image data with geo-information and health data to assess and visualise the personal exposures to the streetscape. Then, this paper explained key aspects of data collection and data fusion processes, which are important in subsequent studies for managerial and practical applications. In summary, this investigation tested the integration of multiple sensors in a pilot study and proved its feasibility. The authors hope that this paper provides knowledge and experience for future applications of personalised sensors for more in-depth analysis.

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CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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ENDNOTES

1 https://www.zephyranywhere.com/
2 https://www.emotiv.com/epoc/
3 https://www.empatica.com/en-int/
4 https://support.microsoft.com/en-us/topic/what-can-i-still-do-with-my-microsoft-band-a2a59355-5be0-3441-9fff-4dc27bcbafb5
5 Narrative Clip was first called "Memoto" and developed in 2012: http://getnarrative.com/
6 GoPro is a world-leading retailer for live-streaming cameras: https://gopro.com/en/us/
7 iON Snapcam, available on Amazon: https://www.amazon.com/iON-Camera-SnapCam-Wearable-Bluetooth/dp/B012X08L0A?th=1
8 FrontRow is a live-streaming wearable camera design from Ubiquiti Labs: https://www.frontrow.com/
9 GPS receiver: http://www.qstarz.com/Products/GPS%20Products/BT-Q1000XT-F.htm
10 Survey Monkey is a tool to help people build a survey for use over the Internet. https://www.surveymonkey.com/
11 The application can be downloaded from here: https://github.com/imranture/E4-TimeStamper
12 https://se.mathworks.com/matlabcentral/fileexchange/53326-cvxeda
13 http://www.ledalab.de/

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