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Assessing personal exposure to urban greenery using wearable cameras and machine learning

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ABSTRACT

Urban greenery is closely related to people's behaviour. With the advancement of science and technology in Artificial Intelligence, wearable sensors and cloud computing, the potential for studying the relationship between people and urban greenery through new data and technology is constantly being explored, such as assessing population exposure to urban greenery using multi-source big data. Taking one individual participant as a case study, this paper proposes and validates the effectiveness of using wearable camera (Narrative Clip 2) and machine learning (Applications Programming Interface of Microsoft Cognitive Service) to assess personal exposure to urban greenery. Microsoft API is used to identify urban greenery tags, including "flower", "forest", "garden", "grass", "green", "plant", "scene" and "tree", in personal images taken by the wearable camera. Personal exposure to urban greenery is assessed by calculating the frequency of the urban greenery tags in all the images taken. Furthermore, the overall evaluation and regularity of personal exposure to urban greenery (including "static exposure" and "dynamic exposure") are explored to identify the characteristics of individual's greenery lifelogging. This study makes a brave attempt that may contribute a new perspective in applying personal big data in studying individual behaviour.

1. Introduction

During the past few decades, urban greenery has been a keyword in city and landscape studies, with discussions emerging regarding how the natural environment influences human health and behaviour. Many theories, such as Stress Recovery Theory (Ulrich et al., 1991) and Attention Restoration Theory (Kaplan & Kaplan, 1989), have also proposed that intensive exposure to urban green space, such as woodlands, parks and gardens, has positive effects on humans' physiological, cognitive and emotional conditions (Maas et al., 2006; Hansmann et al., 2007; Gidlöf-Gunnarsson & Öhrström, 2007). However, while the complicated relationship between urban greenery and human wellbeing has long been discussed, how to track and measure personal exposure to urban greenery scientifically and efficiently is still a new question awaiting in-depth exploration. With the rapid development of technology, novel wearable devices and personal sensors have become ubiquitous in our daily life, and the huge potentials of these new technologies and tools can pave the way for more scientific and technological innovations, which will bring new concepts and opportunities to rethink and verify previous methods and results. Exploring how to take advantage of various devices and methods to promote initial exploration is a common challenge in various fields.

Researchers from the public health domain have called for more attention to the personal level and to monitoring people's daily activities and exposure to greenery to explore more unknowns about human health(Bell et al., 2014), which is consistent with research in urban studies examining the influence of urban greenery on humans. In this paper, unlike empirical studies that employ large samples, we determined to conduct a one-week personal experiment to test our proposed method, which is embracing new technology and a device to effectively measure and evaluate human-scale exposure to urban greenery in the micro-level environment. The results deliver important implications for more possibilities on how we could improve our methodology of assessing personal exposure to the surrounding environment.

2. Related work in the literature

2.1. Measuring exposure to urban greenery

Evidence supporting a positive correlation between urban greenery

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and people's physical and mental health is accumulating. However, limited studies have explored how to quantify population exposure to urban greenery, especially on different spatio-temporal scales (Song et al., 2018). A traditional assessment of urban green environment quality is the green coverage rate (GCR) and greenspace area per capita (GAC), which are commonly calculated as total area of urban greenery divided by land or number of people (Fuller & Gaston, 2009; Yang et al., 2014). Emerging satellite imagery technique and GIS tools have facilitated the assessment of overall urban greenery as well as the distribution and accessibility of urban green space for a given place (Khalil, 2014). Wüstemann et al. (2017) used the urban green space derived from the European Urban Atlas to calculate residents' access to green space within a 500 m radius of their home and found strong disparities in green space provision among German major cities.

A commonly used indicator to describe land cover by vegetation is the Normalized Difference Vegetation Index (NVDI), which quantifies greenery through remote sensing measurements (Smith et al., 2017). de Keijzer et al. (2018) used the NDVI across buffers of 500 and 1000 m around residential addresses to represent older adults' exposure to green space. However, studies have argued that both urban green environment assessment (GCR, GAC) and the NVDI measure urban greenery from an overhead view and thus may missing some eye-level greenery, such as lower bushes, green walls and trees under bridges (Gascon et al., 2016).

Recently, the release of open big data by Internet companies has provided opportunities and a new lens to quantitatively measure the surroundings of urban residents. Google Street View (GSV) is a typical technology that enables researchers to measure street greenery at eye level. Y. Lu et al. (2018) used readily available GSV to develop methods and tools to assess the availability of eye-level street greenery, and the study asserts that GSV can accurately estimate residents' daily exposure to street greenery (Y. Lu, 2019).

Notably, with both the overhead-view urban greenery measured by remote sensing imagery and the eye-level street greenery quantified through GSV, a shared but implicit assumption is that the amount of urban greenery, either in total or on a per capita basis, represents the exposure of urban residents to urban greenspace. Such indicators provide an overall assessment of the quality of a city's green environment but have limited power to reveal people's exposure to urban greenery.

To overcome such limitations, studies have started to study the effects of exposure to urban greenery at finer scales, such as Questionnaire surveys (Groenewegen et al., 2006) and geodemographic data (Barbosa et al., 2007) in the human scale. However, "people living in cities are constantly moving and rarely staying put in the same place all the time" (Song et al., 2018). Except known limitations of accuracy and sample sizes, traditional coarse measurements and statistics ignore the reality that people have their daily activity routines, which would not fully capture human mobility of exposure to the urban environment.

With the advancements of technologies, Global Positioning Systems (GPS) and Location-Based Services (LBS) have provided researchers with precise objective tracks on people's movement, which enables studies to combine measures of urban greenery with the dynamic activity spaces of people (Hirsch et al., 2016). Similar studies are emerging that explore the exposure to urban greenery using GPS-enabled smartphone (Vich et al., 2019), and LBS data from smartphone Applications (Kondo et al., 2020; McEwan et al., 2020; Y. Song et al., 2020). Although the incorporation of such geographical data has improved the preciseness and objectiveness in identifying people's position in the surrounding environment, the quantification of "exposure" individually is still weak.

2.2. Wearable camera as a new tool for collecting personal exposure data

Since the 1980s, microelectronics technology has been developing rapidly. At present, many researchers suggest that, various kinds of commercial wearable devices become more available for the public and have huge potentials in tracking personal exposure and monitor personal health, such as fitness Trackers, smart wristbands and health monitors(Al Jassmi et al., 2019; Berenguer, 2015; Birenboim et al., 2019). Among that, small and light wearable cameras, which can take photos periodically, passively and automatically, providing prominent functions of visual representation of personal behavioural data , since wearable camera can record the front view image directly reflecting what the wearer is exposing to in the surrounding environment. Also , researchers proved that image data obtained from wearable camera had been proved more likely to be true compared with original memory recall and location tracks (Kalnikaite et al., 2010).These recorded images constitute a personal digital recording, with the same implication as "lifelogging" (Dodge & Kitchin, 2007), which means a digital record of personal experience.

With the benefits of technology for image recognition and machine learning, the processing of massive image data has become feasible, effective and efficient, encouraging more attempts to apply the wearable cameras and lifelogging imagery in research of people's daily activities (Duane et al., 2016; Wang & Smeaton, 2013). For example, wearable camera Microsoft SenseCam was applied to record the context of everyday life (Lindley et al., 2009) and travel behaviour (Kelly et al., 2011). Zhou et al. (2019) invited 52 children to wear Narrative Clips to assess children's dietary intake and behaviour.Meanwhile, some studies also adopted wearable cameras to measure personal exposure to the environment (Salmon et al., 2018), such as exposure to alcohol marketing in supermarkets (Chambers et al., 2017) and blue spaces (Pearson et al., 2017) are also being explored. Although wearable cameras have already been adopted in existing studies, most of them just used as an auxiliary tool to supplement the data, few studies regard imagery itself as a kind of data, and mainly focus on the potentials of picture data itself. Actually, each image is ̈a piece of data ̈ containing rich contextual information.

We realize that wearable cameras may offer great opportunities to quantify personal exposure to urban greenery, as they observe urban greenery from the perspective of the wearer by taking numerous photos, which can fill the gap in conventional way of measuring personal exposure to urban greenery in the existing literature. Taking advantage of the advancement of wearable camera and machine learning technology, this paper mainly centres on the research question of how to apply wearable cameras and machine learning to measure personal exposure to urban greenery automatically and effectively, to propose an innovative method to quantify personal exposure to urban greenery rather than general empirical evidence. Using Microsoft API to detect urban greenery from 19,544 images collected from Narrative Clip 2 in one person's daily life, the replicability and universality of our proposed method can be demonstrated from another four participants of different genders, ages, educational backgrounds and occupations. Based on our concept of personal greenery lifelogging, the limitations and merits of the measurement were also discussed at the end.

3. Methodology

Taking advantage of advances in devices and technology, this paper proposes a new methodology to simplify the process of tracking personal greenery exposure and improve the accuracy and effectiveness of the analysis (Fig. 1). The methodology consists of the following four major steps: 1) Carrying out a one-week participant trial by outfitting participants with a wearable camera three times in consecutive months, through A total of 19,544 personal exposure images were collected in total. 2) After image cleaning, detecting elements in the images that represented urban greenery, such as tree, brush and flower, through Microsoft API. 3) Analysing and visualizing the result to identify the regularity of one-week exposure and analyse the characteristics of how it occurs (either 'static exposure' or 'dynamic exposure'), then comparing the differences in urban greenery exposure under various weather conditions. 4) Validating the accuracy and feasibility of the proposed method by comparing the results with memory recall and manual audit.

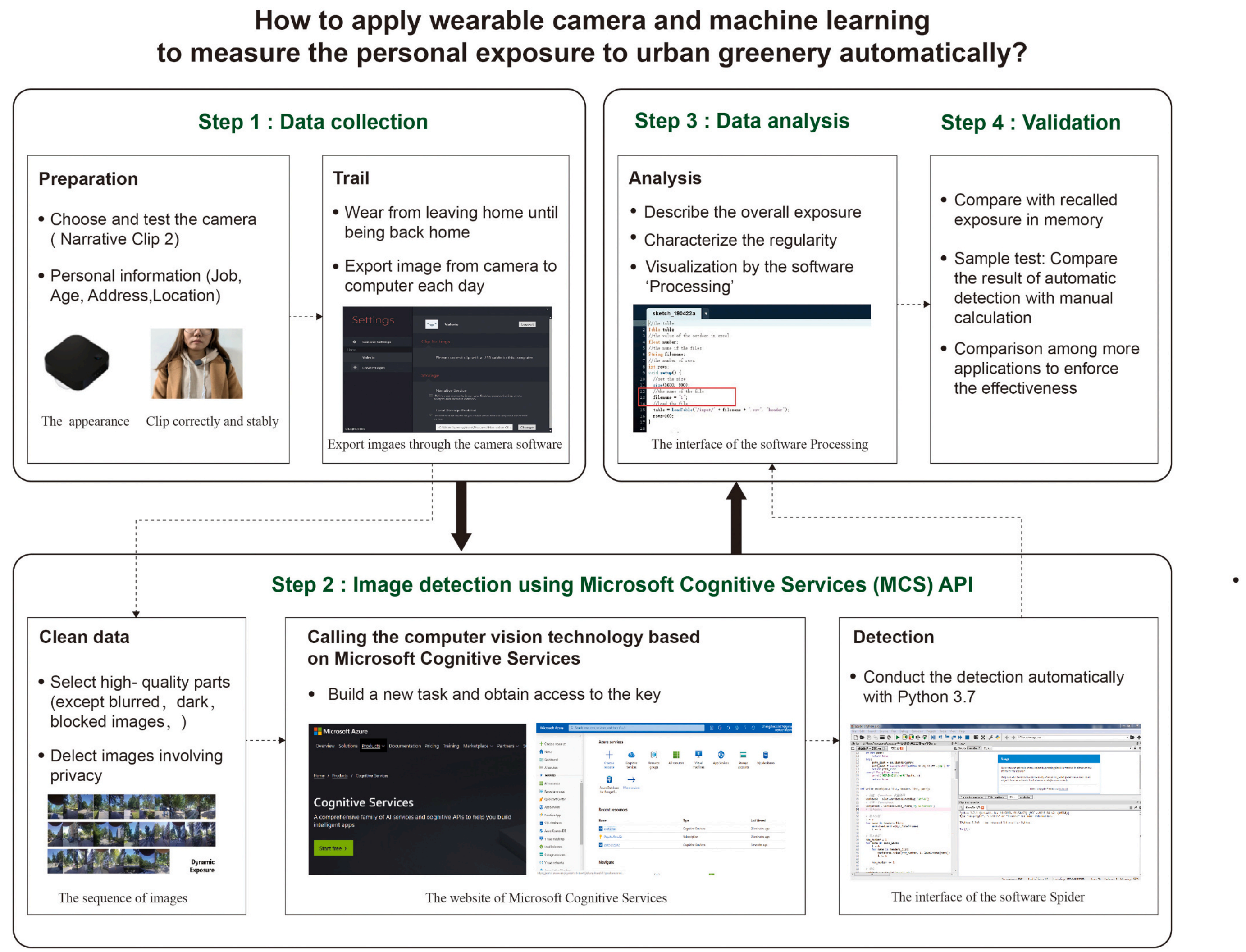

Fig. 1. Methodology of this study.

4. Data collection, processing and analysis

4.1. Introducing the wearable camera: Narrative Clip 2

As a type of human sensor, a wearable camera incorporates cutting-edge technologies to self-review daily life visually with user-friendly operation. The commonly seen commercial wearable cameras on the market include SenseCam[1] and Gopro,[2] which are used extensively in current personal health care research. In this study, a wearable camera named the Narrative Clip 2 was adopted to collect personal exposure images. Compared with SenseCam and Gopro, the Narrative Clip 2 is superior in its tiny size and lighter weight. Additionally, since the Narrative Clip 2 can be clipped onto clothing, it is more stable and less noticeable than SenseCam. The Narrative Clip 2 is also more cost-effective than Gopro.

The Narrative Clip 2 was first produced in 2012 and is currently in short stock around the world, but some newly commercial wearable cameras are available on the market now, such as iON SnapCam[3]and SereneLife[4], which have similar size and appearance to Narrative Clip 2, also support high-quality images for lifelogging recording. The original concept of the Narrative Clip 2 is a lifelogging camera that can automatically capture video and images of the wearer's daily life, so everyone can tell their own story through their lifelog. However, limited by the cost and short stock, we could only obtain one device at this stage and therefore could only record one participant's consecutive personal exposure images for this pilot study. The specifications of the camera are listed in Table 1 below. During the study, the participant was required to wear the camera on the collar in a fixed and stable position to capture the front view. To guarantee the readability of the images, the participant had to ensure that the lens of the camera was not blocked by other objects, such as a jacket or hair. The design and operation of the camera is simple and user-friendly; there is no button beyond the power switch,

[1] Sensecam is a wearable camera developed by Microsoft in 2004, which contains a number of different electronic sensors and can take images automatically. Information is available on the website: https://www.microsoft.com/en-us/research/project/sensecam.

[2] Gopro is a versatile camera with a small size; it captures moments in various situations and supports 1080p in images and videos. Information is available on the website: https://gopro.com/en/us/shop/cameras.

[3] SnapCam allow people capture all of life's moments, support a high-resolution (8 megapixel) image and video model, and 10s/30s/1 min time-lapse shooting. More information: https://uk.ioncamera.com/snapcam-retailers/.

[4] SereneLife support 1080p Full HD with Built-in Wi-Fi, Ideal for Classroom to Record the Lecture, Sports, Jogging, Cycling, Hiking, Fishing, and Camping. More information: https://serenelifehome.com/.

Table 1
Technical specifications of the camera.

Image	Specification	
	Weight	19 g
	Price	$199
	Period sold	2014–2019
	Original name	Memoto
	Camera Sensor	8MP/1080p Video
	Camera Aperture	f/2.2
	Lens Diagonal FoV	86°
	Resolution	3264 × 2448 (4:3)
	Storage	Stores up to 4000 photos or 80 min of video
	GPS	Built-in

(Source: http://getnarrative.com/)

and it automatically starts shooting images when the power is on, so the participant only needed to clip it to the right place. Meanwhile, there is a built-in light-sensor, which enables the camera to stop shooting in a dark environment as there is no flashlight. Each day before wearing the camera, the participant had to make sure it was fully charged to enable consecutive shooting for as long as 12 to 15 h. Likewise, after wearing the camera, the images had to be exported in time to leave sufficient space on the memory card for the next day's recording. When the power is on, the Narrative Clip 2 takes a picture every 30 s to record the front view of the wearer, resulting in an average of 1000 photos each day assuming 9–10 h of wear time.

4.2. Participant's information and data collection

The participant was recruited in August 2018 and was asked to wear the camera for one week each in August, September and October. Before the participant began wearing the camera, we conducted a short interview with the participant to acquire some basic background information and provided guidance on using the Narrative Clip 2 for data collection. The participant was a 27-year-old female who worked at a university and lived close to the campus. The individual usually walked or cycled to work and spent the entire day on campus during workdays and had lunch and dinner at the canteen on campus as well. She noted that her daily activities were within a 2000-m life circle around her home.

Because the purpose of wearing the camera was to record the participant's exposure to the environment, especially urban greenery, the participant usually began wearing the camera at 8:00 each day when she left for work and did so until arriving home in the evening, which was between 19:00 and 23:00. During the wearing time, the participant had to clip the camera onto her collar and ensure it faced the same direction when she moved. The participant could decide when and where to wear the camera; she could remove it if she felt uncomfortable or that it was inappropriate to wear on some occasion. Additionally, for privacy reasons, the participant could decide which images would be deleted before submitting them. The camera-wearing experiment protocol and images collected by the camera each day during the experiment are described in Fig. 2, this paper takes data from August to October to evaluate the overall level of urban greenery exposure, and one week data in October to describe the characteristics of the greenery exposure more specifically.

4.3. Image detection using Microsoft Cognitive Service API

Applications Programming Interface (API) is a computing interface that allows third parties to use the functionality of certain software applications. In this paper, we take advantage of Microsoft Cognitive Services to apply the computer vision technology (https://azure.microsoft.com/en-us/services/cognitive-services/). Microsoft Cognitive Service (MCS) based on cloud computing, brings artificial intelligence technology and machine learning to every developer without professional backgrounds by calling an API, which is less expensive and more secure and reliable than a personal hard drive. Microsoft API provides access to advanced machine learning algorithms that process pictures and videos at high speed, then extract and return rich information to users, including tagging visual features, detecting objects and describing images. Users can connect to the embedded AI function by calling API,

b) Records of photos taken during the period of data collection

Month	Date	Valid images
August	21/08/2018	1,352
	22/08/2018	Did not wear
	23/08/2018	1,076
	24/08/2018	600
	25/08/2018	1,122
	29/08/2018	403 (battery died)
	31/08/2018	1,439
September	02/09/2018	1,034
	03/09/2018	1,454
	04/09/2018	730
	05/09/2018	920
	06/09/2018	Did not wear
	07/09/2018	954
	08/09/2018	Did not wear
October	08/10/2018	1,272
	09/10/2018	1,454
	10/10/2018	1,409
	11/10/2018	1,287
	12/10/2018	1,254
	13/10/2018	531 (battery died)
	14/10/2018	1,253
In total		19,544

Fig. 2. Camera-wearing protocol and personal information.
Notes: Fig. 2-a) shows how the participant wore the Narrative Clip 2 and presents a sample image taken; Fig. 2-b) presents the records of data collection during wearing. During the data collection, since the camera wearing was not intended to increase the participant's burden, on some days, she could decide not to wear it or take it off if she felt wearing it was stressful or inappropriate for her work.

even researchers without machine learning expertise, in a simplified method to realize automatic image detection using machine learning.

As shown in Fig. 3, this process aims to identify and tag visual features in the images, which are further used to measure the exposure to urban greenery. Before calling the API service, users must register on the website of Azure for all services. Each new customer receives a free account to call for the API service within one month; after that, the price for 1 M transaction is approximately 1 U.S. dollar. After entering the

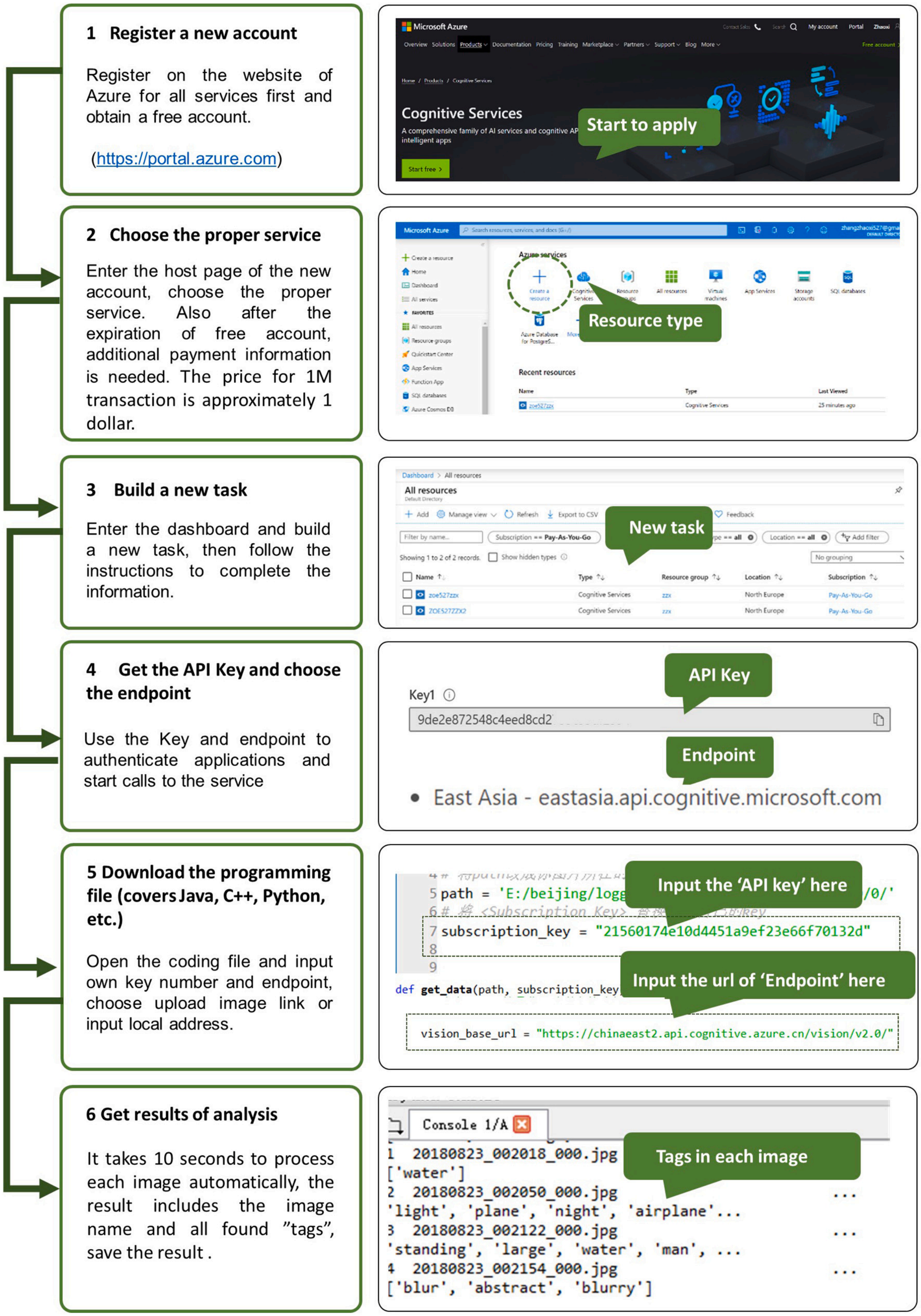

Fig. 3. Process of Microsoft API image detection.

dashboard, users can build a new task and choose the desired service, and then they will obtain access to the request key number, which is provided after calling. Then, users choose the programming language (e.g., Java, C++, Python) and API console, making sure to select the correct location for this resource (e.g., Australia East, Central Unite State, West Europe). After this preparation, users can upload an image resource or link to the local image folder and wait for the result, usually including the image name, identification of all "tags", and simple descriptions. This paper used Python to process the images, and it usually took 10 s for each image to be processed. In total, forty hours total were spent for all the images.

4.4. Data analysis

According to the results of MCS API identification, we achieved more than 200 types of tags in these images. The tags are further classified into indoor or outdoor environment, with outdoor tags including trees, cars, water, pavement, and building and indoor tags including lamp, table, window, and wall. As shown in Fig. 4-a), the tags are connected with other information from each image, such as location, time and event, to determine the motion and current circumstances of the participant. In addition, 8 types of outdoor tags are selected to represent urban greenery, including "flower", "forest", "garden", "grass", "green", "plant", "scene" and "tree", as shown in Fig. 4-b).

If one or more urban greenery tags are identified in an image, the urban greenery index for the image is defined as 1; otherwise, it is 0. That is, the result of the tag analysis is always binary, either 1 or 0 for each image. Finally, the result of the tag analysis is visualized to reflect the characteristics and potential regularity of the participant's exposure to urban greenery. As shown in Fig. 4-c), the images with urban greenery as 1 are coloured green, and a slide bar is created to visualize the time and period that the participant is exposed to urban greenery. Checking the results of the visualizing slides with the original image database, we find four periods of urban greenery exposure: the morning and late afternoon commute between home and work and the round trip to lunch. Following this approach, this paper explores the fundamental rules or regularities of personal exposure to urban greenery based on the weekly dataset.

5. Results

5.1. Overall evaluation of personal exposure to urban greenery

Based on the results of detection and aggregations of total occurrences of greenery-related tags, this paper evaluates the degree of daily exposure to urban greenery by counting the number of images with greenery identified. This paper evaluates the overall level of urban greenery exposure from August to October by comparing the frequency of "Greenery" (the proportion of images with greenery), also taking the frequency of "Outdoor" as a reference, and calculates the ratio of "greenery" to "outdoor" as well describing the degree of personal exposure to greenery when remaining outdoors. The results show that

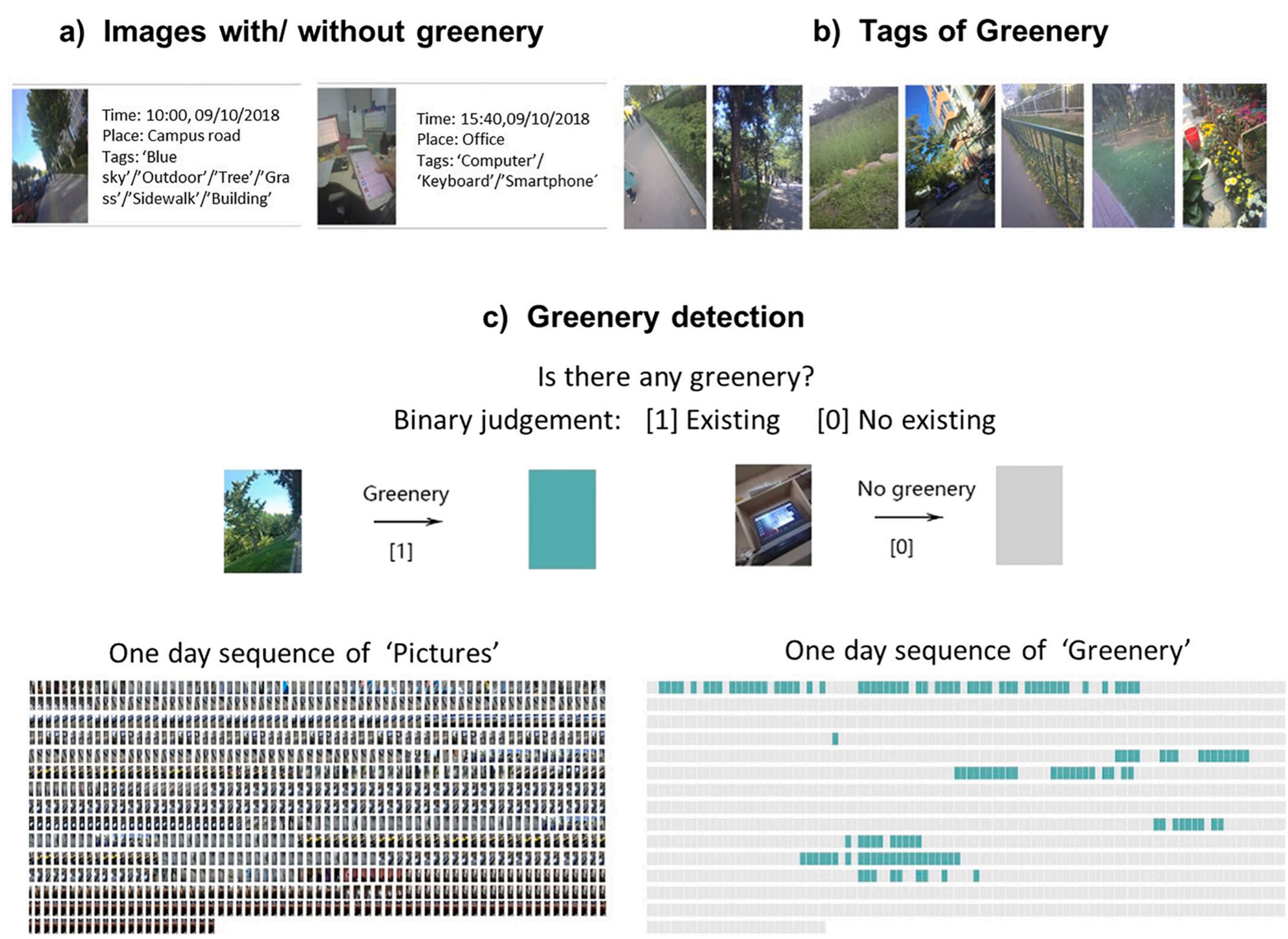

Fig. 4. Greenery detection and data analysis.
Notes: Fig. 4-a) on the upper left provides two sample images with and without urban greenery; 4-b) on the upper right presents sample images of the types of urban greenery tags that appeared; 4-c) on the bottom is the generation of the description of greenery exposure.

the wearer went outdoors more frequently and had higher average exposure to urban greenery in August, and then the rate decreased in October. However, the rate of greenery exposure and ratio of “greenery” to “outdoor” increased, which implies that the wearer sought more closeness to greenery when she went outdoors in October. The purpose of staying outdoors for more exposure to greenery may become a driving force during autumn. Fig. 5 shows that the average exposure time to greenery accounted for 15% of the participant’s entire daily routine but accounted for a large percentage (60%) of outdoor time, which suggests personal exposure to greenery is higher.

5.2. Greenery lifelogging: ‘static exposure’ and ‘dynamic exposure’ to urban greenery

This paper focuses on exposure to urban greenery during a week in October, with the green sections also indicating the images identified as greenery. During weekdays, high greenery exposure usually appears in commuting, eating out, going out and leisure time. The results show that the average proportion of greenery exposure was approximately 10% of the wearer’s active time, while this ratio increased to 11.6% on Sunday. Additionally, we find that some places or routes appear in the images repeatedly and continually, which indicates that some fixed places and routes with corresponding exposure often occur simultaneously and regularly; as a result, this paper separates the exposure into “Static exposure” (Green Place) and “Dynamic exposure” (Greenery Path). As Fig. 6-a) and 6-b) show, “Static exposure” means remaining in a place surrounded by or adjacent to brush and trees more frequently since some leisure places, such as lotus ponds and grassy areas, are found in the image data, which indicate the individual liked to stay there for longer time. “Dynamic exposure” means exposure to greenery during movement. It is clear that the contents in the continuous image sequence also occur consistently, meaning that exposure to greenery was consistent and kinematic.

According to the results of API calculation and manual inspection, it is possible to identify how the two types of exposure alternate and the characteristics of personal exposure. In Fig. 6-c), the slides of “Static exposure” and “Dynamic exposure” are labelled in the one-week greenery exposure. It is shown that dynamic greenery exposure usually occurred regularly on weekday mornings, while static greenery exposure usually occurred during weekends, and the duration was always longer than on weekdays. As the participant recalled, she usually cycles or walks along urban roads with trees and enters the campus through the east gate of the university, and the greenery level on campus is obviously higher than outside it, which increases her exposure to greenery. The results show that dynamic exposure made up a large percentage of her daily exposure to greenery, which can be interpreted to suggest that the individual did not have sufficient opportunity to remain for long times in a green environment. However, the manual inspection reveals some inconsistencies (grey-coloured slides) with the API calculation. These occur because API can mistakenly identify objects and categorize indoor plants or greenery outside windows as outdoor greenery. Finally, each tiny part of the participant’s daily exposures forms a digital recording of her lifelogging of ‘Greenery’, including every fragmented information such as time, duration and condition of the exposure, describing and representing the personal exposure systematically and completely.

6. Validation

6.1. Validating effectiveness: comparison with memory recall

The results allow easy identification of the regularity of personal exposure to urban greenery. In the interview, the participant said that she could only remember some green spaces in which she usually stayed but had a blurry memory regarding her degree and frequency of exposure to urban greenery.

Compared with the participant’s personal memory recall of her exposure (Fig. 7), the wearable camera used in this study provides a more detailed description of her exposure and reduces the effort required in data collection since a wearable camera is conducive to self-tracking over a long time period with more detail and machine learning enables effective detection and analysis of these images. More important, although the participant could recall some locations with impressive urban greenery, she had difficulty remembering the specific time and duration of the exposure, especially for some fragmented times during daily activities, such as commuting. There is potential for some degree of underestimation or overestimation of personal exposure, suggesting that the participant lacked the ability to recall much of her own exposure to urban greenery. The results of the wearable camera and machine learning provide an means of effectively evaluating the degree and reflecting the characteristics of personal exposure to greenery.

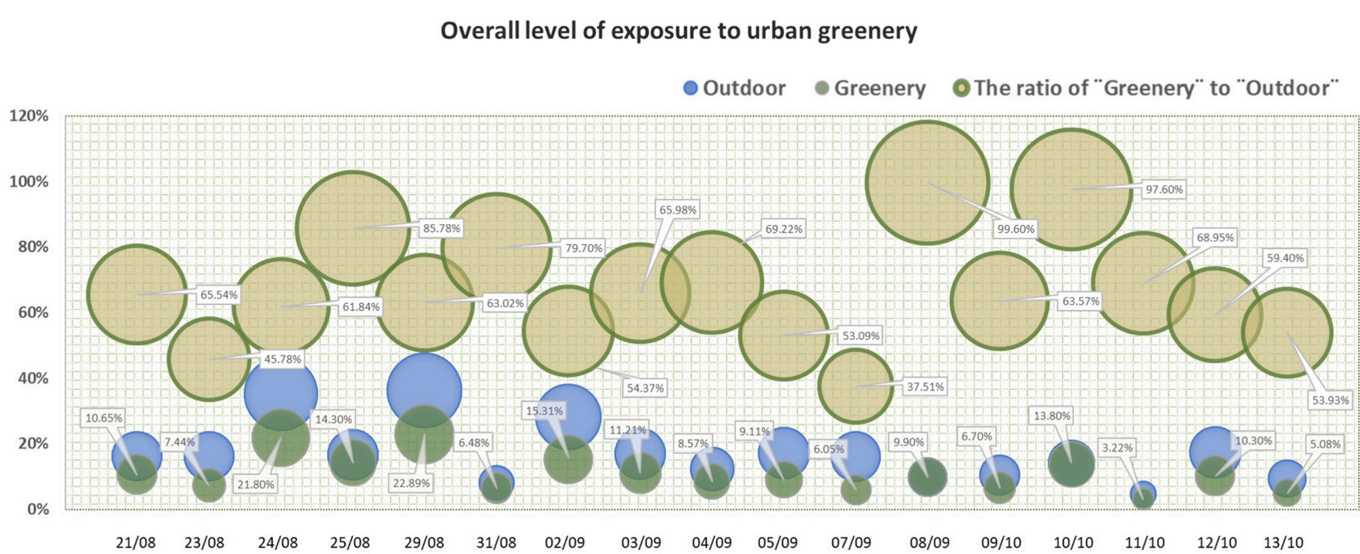

Fig. 5. Greenery detection and data analysis.
Notes: a) “Outdoor” means the proportion of staying outdoors through reading the contents of images, the proportion of outdoor = images taken outdoors/ total image number. b) “Greenery” means the proportion of images with greenery through API detection, the proportion of greenery = images with greenery/total image number. c) The ratio of “greenery” to “outdoor” = images with greenery/ images taken outdoors, implying the degree of exposure to greenery while outdoors.

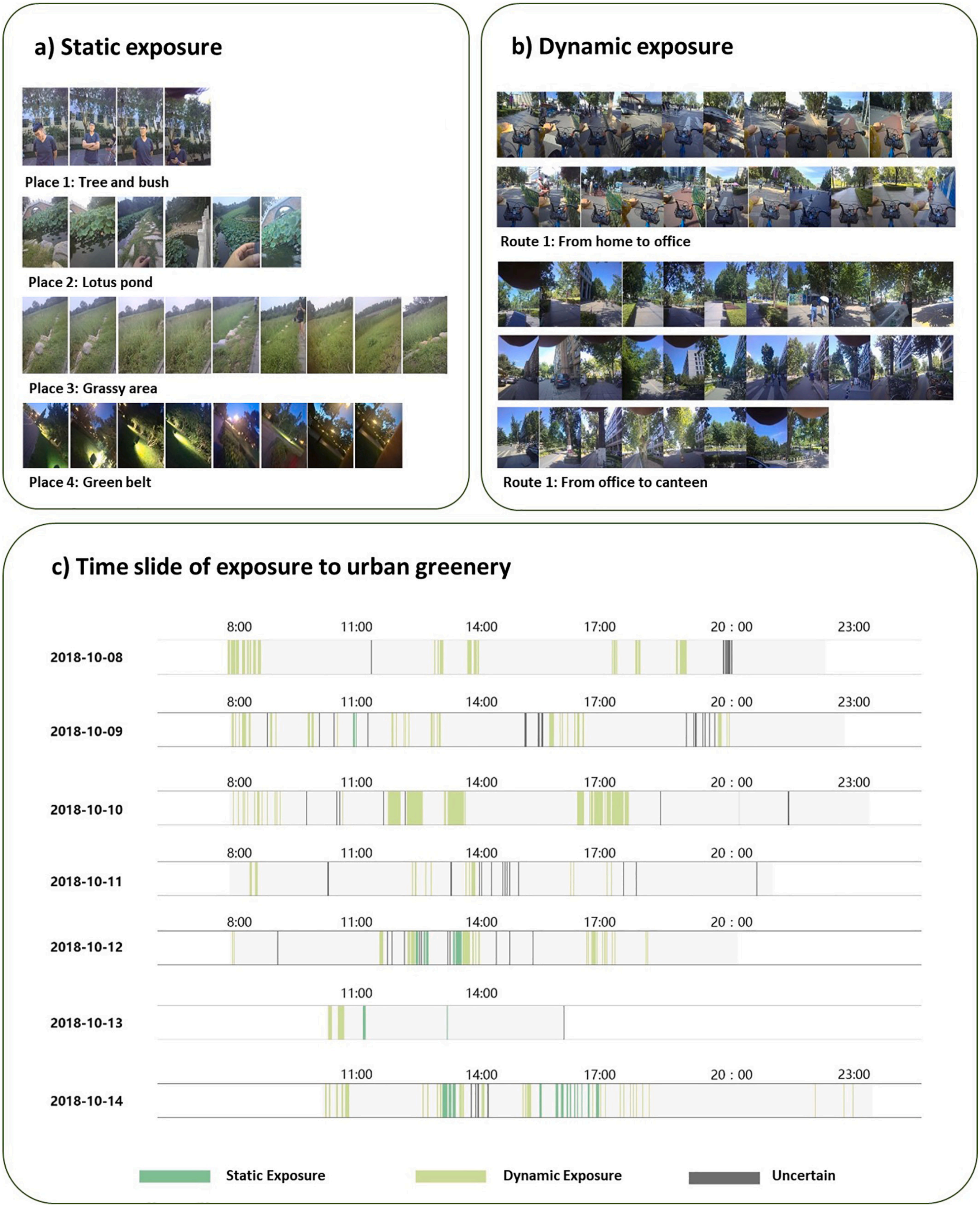

Fig. 6. Static and Dynamic exposure to greenery.

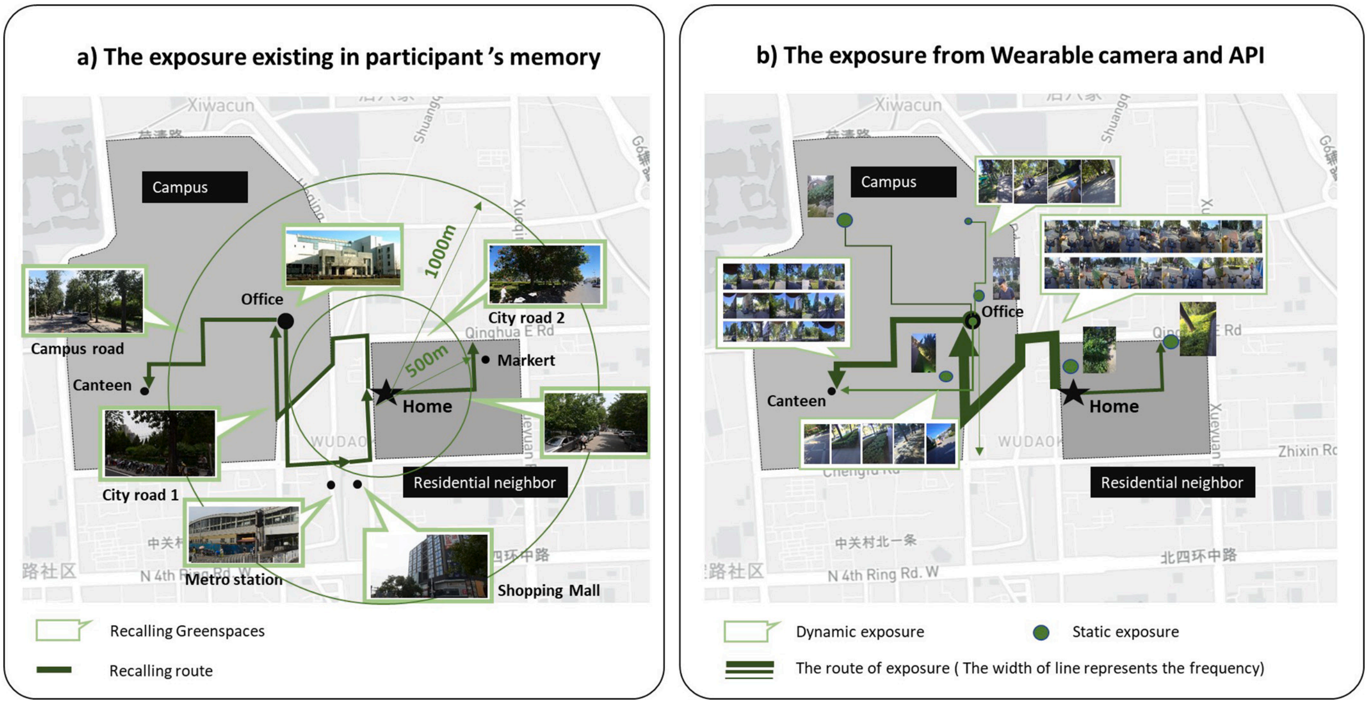

Fig. 7. Comparison between recall and wearable camera.

6.2. *Validating accuracy: comparison with manual audit*

This paper employed a wearable camera and Microsoft API to obtain and detect the images automatically, and for validation purposes, we conduct a 10% sample test. From each day's images, we randomly select one from every ten to build a test group, examining the image by manual audit and comparing it with the previous machine learning result. Browsing the results, because we find that errors occurring during both taking photos with the wearable camera and API detection influence the accuracy, the validation is focused on image quality and the detection of API. Image quality is evaluated by the proportion of low-quality images, including blurred images caused by fast movement and weak light during the night, and incomplete images caused by objects blocking the view, such as hair, a scarf or a collar, and items in hands. In Fig. 8, the results show that the main problem affecting the quality of images in the study is the view blocked by other objects, while blurred images account for only a small percentage of the total. That is, a wearable camera is a reliable and effective way to capture images, and the key is to wear it correctly and keep the lens free of blocking objects. Second, the detection of API is evaluated by the proportion of errors from "fail to detect the greenery that actually exist in the images" and "regard other green-coloured objects as greenery mistakenly". The results show that the total error rate is approximately 8%–10%, and the difference between the two types of errors is not obvious, which means the chances of both types of errors are similar due to the shortcomings of the API system. We also find that the camera angle and perspective may influence the results. Even if some blockage exists, as long as the images are readable and the crucial elements are still visible, the API can still work, but the perspective of images will influence their content, which reduces the accuracy.

6.3. *Validation of the universality and feasibility of the method*

To counteract the potential bias from the participant in terms of age, gender, education, occupation, etc. and to validate the universality and feasibility of the proposed method in this paper, 4 more participants with different socio-demographic backgrounds (Fig. 9) were recruited to wear the Narrative Clip 2 for one week. In addition, one more student auditor without a programming background was recruited to perform the API detection for the first time. More experience from this extension of the application shows that whether for a courier who travels around a city and spends most of the daytime outdoors or a SOHO white-collar worker or college student who leads a moderate lifestyle and stays indoors more, a wearable camera works well in various situations. Additionally, images from retired older adults illustrate that wearable cameras are also user-friendly and easily operated by seniors. It is clear that the wearable camera can be applied in various situations by different people to explore the regularity and characteristics of personal exposure. Furthermore, with Microsoft API, the process of extracting information from images can be simple and fast, making it possible to handle larger numbers of images in group studies, even for novices without professional knowledge. However, in addition to the automatic detection of tags in images, the accuracy of API detection must be improved in the future by the inclusion of self-training tags. Therefore, use of wearable cameras and API helps conserve effort in collecting and analysing personal tracking data and satisfy the purpose of measuring and evaluating personal exposure to urban greenery.

7. Discussion

7.1. *Academic contributions*

Overcoming the limitations of the traditional measurement of exposure to urban greenery, this paper focuses on the human scale and micro-environment, provides a fresh angle to observe and track personal exposure to urban greenery by collecting high-resolution picture data. This is our first attempt to adopt wearable camera into personal exposure analysis, thus the purpose of this study focused on the improvements and explorations of the methodology part. Focus on the value of image itself, this paper tests a new method to extract and analyse rich contextual information from continuous time-lapse personal imagery effectively, and applies them to objectively evaluate personal exposure to urban greenery. At the individual level, the results also reflect the regularity of personal exposure to urban greenery and present the

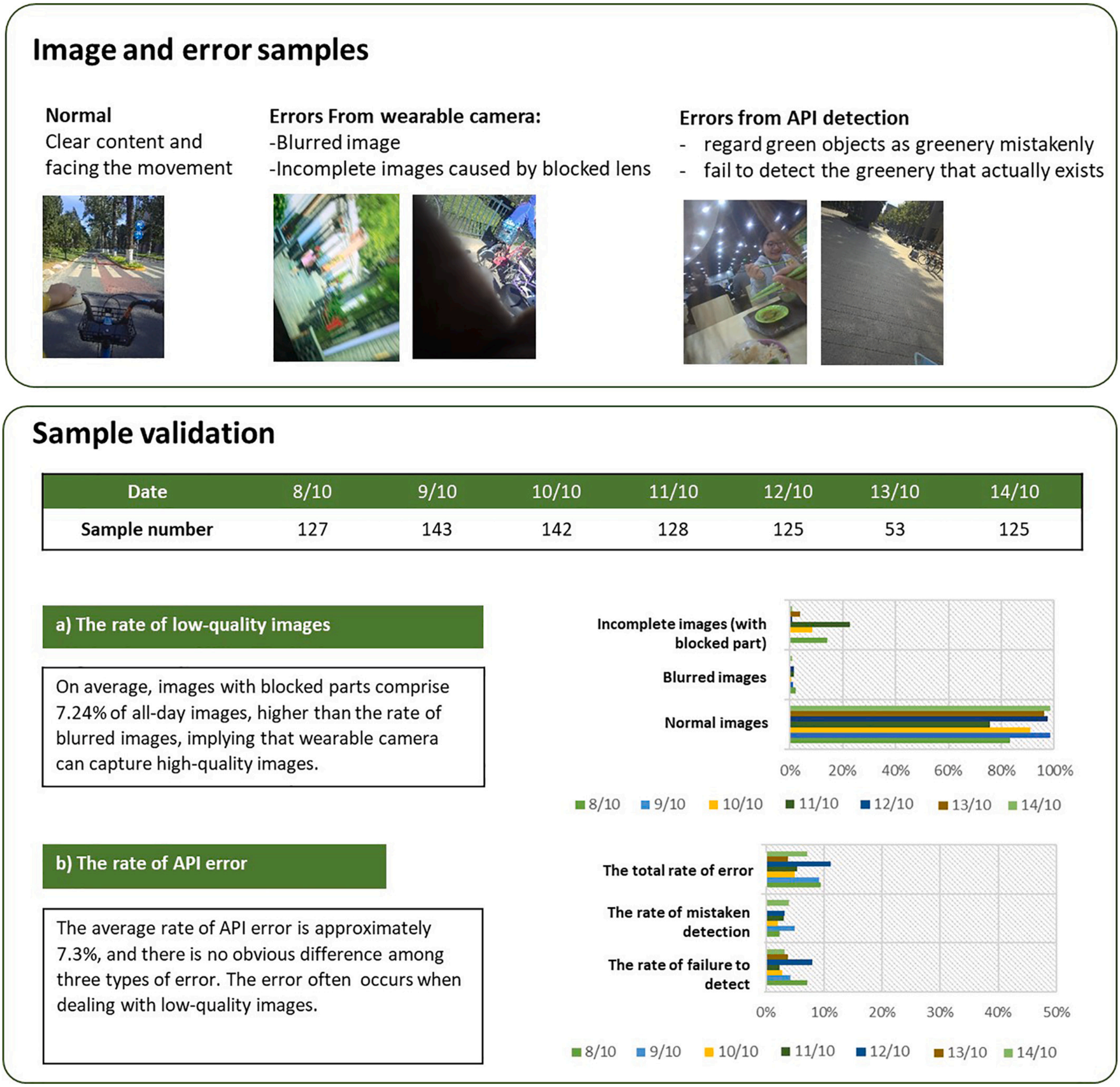

Fig. 8. Manual audit for validating the detection accuracy.
Notes: a-1) The quality of the wearable camera images is validated through evaluating the rate of two low-quality images: blurred images and incomplete images caused by blocking objects. 2) Calculation of the rate of low-quality images: Rate of incomplete images = number of images with blockages/ total number of sample; Rate of blurred images = number of blurred images/ total number of sample.
b-1) API is validated by evaluating the rate of errors during the detection: failure to detect greenery that actually exists in the images and mistaken detection of other green-coloured objects as greenery. 2) Calculation of the rate of API error: Rate of failure to detect = number of images with greenery but without greenery tags/ total number of sample; Rate of mistaken detection = number of images without greenery but with greenery tags/ total number of sample. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

characteristics of personal greenery lifelogging in daily life, although the limited sample size may weaken our findings.

The highlights of this paper are still worthy to be mentioned:

- To our knowledge, this is the first attempt to adopt a wearable camera, the Narrative Clip 2, to track personal greenery exposure by analysing continuous imagery in urban setting.
- Taking advantage of Microsoft Cognitive Services to simplify the application of machine learning in detecting ̎greenery̎ in numerous images, which significantly reduces the technical barriers for people without relevant skills.
- Applying the concept of measuring and evaluating ‘Greenery lifelogging’ to represent the regularity and characteristics of personal greenery exposure, which can potentially be applied in other practical areas as well.

Last but not least, the effectiveness of our methodology has been validated in this study, while evidences with more participants are

Job	Gender	Age
Courier	Male	30
Pensioner	Female	84
SOHO	Female	27
Student	Female	23

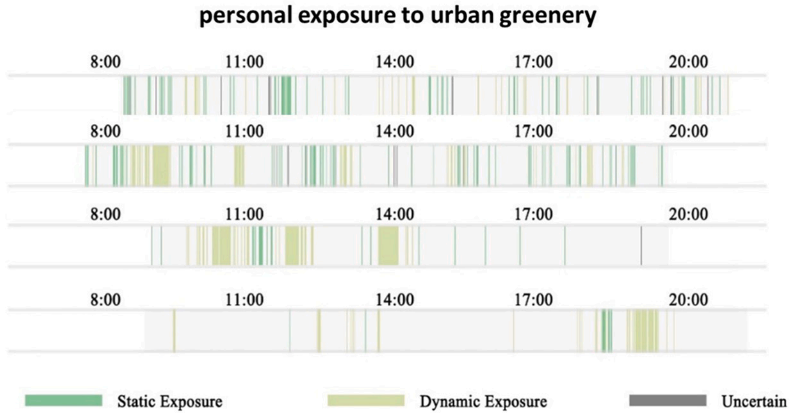

Fig. 9. Comparison among other 4 participants' one-day exposure.

expected in the future. We hope further studies of measuring exposure to urban greenery from micro and humanistic perspectives can provide a deeper interpretation of individual exposure to greenery, especially for interdisciplinary research.

7.2. Limitations

Despite merits above, there are still limitations of this study. Due to the high price and limited stock of the Narrative Clip 2, it was not possible to recruit a large number of participants to join this study during our experiment, this pilot study takes one participant's data as an example to illustrate the method proposed, which is the main limitation of this paper. Although this paper conducted a long-term tracking of the same participant in August, September and October to guarantee that a sufficient number of images were collected and tested the possibility of long-time usage of the device in daily life the possibilities of larger scale recruitment need to be tested.

Another limitation was certain effects of the wearable camera and calling API. Some problems with image quality occurred as a result of the following limitations of the Narrative Clip 2:

- Poor light sensor of the lens delivers low-quality images in dark situations;
- Lack of anti-shaking function, as a result of which clear images cannot be captured during intense movement;
- The limited battery life makes it difficult to support long periods of shooting, and there is no warning tone of low battery; as a result, sometimes the camera may be already dead with no notification;
- The angle of the camera is difficult to control to always face the front; sometimes the camera may face the ground or sky during movement and fail to capture the surrounding greenery;
- Hair and scarves or other accessories will block the lens, which lowers the quality of images;
- There is a single function without more sensors to record locations, time-stamp images, and monitor other environmental details, such as temperature and humidity.

The study has proved that images quality is the key factor in greenery analysis, which will influence the result of API detection. Regarding calling API to process images, the limitations mainly stem from two aspects of the API system: sometimes it fails to detect greenery that actually exists in images, and sometimes it mistakenly regards other green-coloured objects as greenery. The limitations of API detection can be overcome by optimizing the API function and creating new tags suitable to individual projects.

7.3. Next steps for improvement

Considering the limitations of this paper, it is necessary to improve the method before carrying out more studies. First, since the added value of our paper is to test the effectiveness of using wearable camera and continuous imagery recoding rather than only Narrative Clip 2 product. More available portable image and video recording devices can be considered as the replacement of the Narrative Clip 2, and possible options as following:

- Test other available commercial cameras such as SenseCam, iON SnapCam and SereneLife mentioned above. Since iON SnapCam and SereneLifea are more affordable than Narrative Clips, it is possible to employ large samples and acquire more empirical evidence.
- Cameras with video recording function such as Gopro, can be installed on vehicles, motorbikes and bicycles to study the personal exposure of greenery under different models of movement.

Secondly, multiple types of personal sensors can be combined with a wearable camera, such as GPS, accelerators, eye trackers and personal health monitor sensors, to measure more dimensions of personal exposure to greenery.

7.4. Potential applications

The concept of personal exposure to urban greenery can also be applied in other aspects of personal environmental exposure and increase people's knowledge of their surroundings and themselves. To simplify the procedure and process of calculation, our research team developed a project named "Life Log Calculator" to calculate the multiple exposure rate to the environment (as shown in Figure Appendix Fig. 1), which provides six types of pre-set classifications: 'city', 'traffic', 'outdoor', 'screen', 'green' and 'food'. After the results of API analysis were uploaded, the program calculated the exposure degree, and an answer window popped up containing the results.

However, potential applications of interdisciplinary operations require more attention in urban environmental studies. As wearable cameras not only contribute to deep knowledge of individual exposure but also provide perspective on lifestyle and habits, this cutting-edge method enables us to know more about the real spatial-temporal relationship between individuals and cities. For example, the paper mentions static and dynamic greenery exposure; if larger numbers of cases show similarities in choices and habits in exposure of greenery, it will be possible to rethink the distribution of greenery in cities and attempt to increase exposure by changing the organization of green space. Therefore, this new device and technology can provide technical support for site study, such as urban spatial evaluation and route selection of pedestrians. We expect that more research will take advantage of wearable cameras and new technology to study personal exposure and environments in urban space.

8. Conclusions

This research proposes an easy method to measure personal exposure to urban greenery by means of wearable cameras and calling Microsoft API machine learning. The method proved that a wearable camera can record abundant imagery of an individual's exposure to greenery automatically and passively, along with the technology of image detection, which help understand the role of greenery during individual lifelogging. The results evaluate the overall level of greenery exposure and show the regularity and characteristics of different types (Static exposure and Dynamic exposure) in daily life and tendencies in various seasons, also representing the variety among different people. This paper is beneficial in capturing and evaluating the level of greenery exposure from a personal and microenvironment perspective, which will lead to more exploration in interdisciplinary fields involving the urban environment and personal exposure.

CRediT authorship contribution statement

Zhaoxi Zhang: Methodology, Writing - original draft, Data curation, Visualization, Software. **Ying Long:** Conceptualization, Resources, Supervision, Project administration, Funding acquisition. **Long Chen:** Writing - review & editing, Validation. **Chun Chen:** Software, Visualization, Validation.

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.

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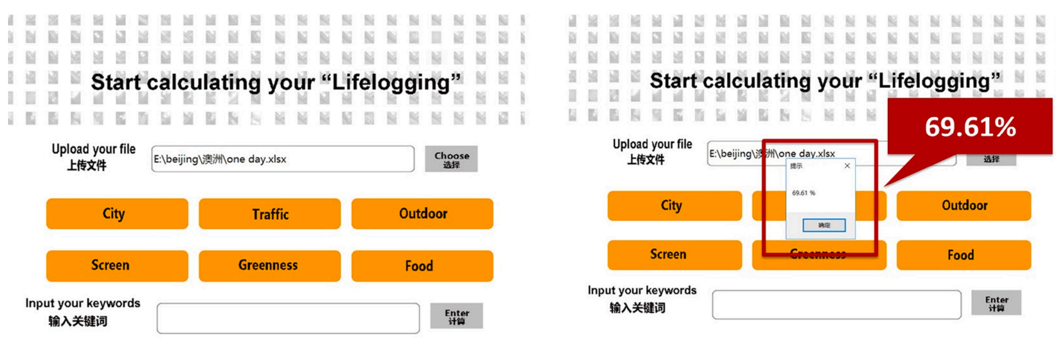
Appendix A



Appendix Fig. 1. "Life Log Calculator".

To simplify the procedure and calculation process, a project named "Life Log Calculator" was developed by our research team; it is a PC program that can calculate the rate of exposure to the environment based on JAVA language. In this program, we provide six types of pre-set classifications as the buttons show, the program calculates the exposure degree, and then a results window provides an answer. As the example shows, the urban exposure of this individual has reached 69.61%. At the same time, the calculator also supports user-defined search. In the keyword interaction window of the software interface, users can customize search labels, such as more specific foods (banana, apple, etc.), and type these words in the interaction window connected by "&". The calculator will search all the provided keywords and produce a result. The calculator is designed for wearers or other experts, helping users know themselves or their research groups more effectively and accurately.

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