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Measuring individuals' mobility-based exposure to neighborhood physical disorder with wearable cameras

Wenyue Li [a], Ying Long [a,*], Mei-Po Kwan [b,c], Ningrui Liu [a], Yan Li [a], Yuyang Zhang [a]

[a] School of Architecture and Hang Lung Center for Real Estate, Key Laboratory of Eco Planning & Green Building, Ministry of Education, Tsinghua University, Beijing, China

[b] Department of Geography and Resource Management and Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, Hong Kong, China

[c] Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, 3584 CB, Utrecht, The Netherlands

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ABSTRACT

To date, most studies have assessed individual exposure to neighborhood physical disorder (NPD) through the static residence-based approach, which ignores elements of human mobility and may lead to inaccurate estimates. This study assessed individual exposure to neighborhood physical disorder through the mobility-based approach using wearable cameras. The use of this approach allowed us to leverage innovative tools to accurately assess exposure to NPD in individuals' activities in space-time. We assessed the volunteers' exposure to neighborhood physical disorder by manually auditing pictures taken by wearable cameras on an online browser-based assessment platform. The results illustrated that wearable cameras can clearly capture the exposure while volunteers were engaged in travel behaviors. We also compared the proposed approach (mobility-based, using wearable cameras to take photos) with other approaches (with consideration of travel behaviors to varying degrees, using street view images) to demonstrate that wearable cameras can record individual exposure to neighborhood physical disorder accurately and conveniently, and the assessment results might be significantly different from those obtained by other approaches. Thus, the proposed approach is of great significance.

1. Introduction

The concept of neighborhood disorder includes both social and physical characteristics, among them is neighborhood physical disorder (NPD), which is the focus of this paper. NPD is defined as places with "visual signs of negligence and unchecked decay" (Skogan, 1990), which are indicators of the low-quality built environment. In 1982, Wilson and Kelling (1982) proposed the "broken window" theory, which posits that disorder in urban neighborhoods leads to an increase in serious crime. The theory brought further discussion about the impacts of NPD on neighborhoods and their residents and has attracted the interest of scholars, particularly in the field of public health.

According to broken window theory, NPD influences health outcomes in three ways. The first is direct in that a broken window means there are fewer eyes to monitor peoples' behavior, which leads to higher rates of crime, vandalism, and risky activities. The second influence, fear, causes a decrease in physical activity and, hence, leads to health problems (Cunningham-Myrie et al., 2015; Dulin-Keita et al., 2013; Mendes de Leon et al., 2009). The third impact, omnipresent stressors, increase the risk for individual mental health problems and may lead to social isolation (Warr et al., 2009; Bierman, 2009; Pai & Kim, 2017; Natsuaki et al., 2007; Tao et al., 2020). Both the second and third influences are indirect but support the theory that NPD influences health outcomes by instilling fear in individuals who interpret it as a sign of danger and, thus, retreat socially (Jacobs, 1961; Wilson and Kelling, 1982). However, meta-analysis has shown that the evidence of NPD's health impacts is insufficient or inconsistent (O'Brein et al., 2019); thus, there are gaps in assessing the relationship between NPD exposure and health outcomes. This paper focuses on the assessment of individuals' NPD exposure as a more accurate exposure assessment may help improve the research related to the health outcomes of NPD.

Accurate assessment of NPD is critical to evaluating its influences on human health. To assess the degree of NPD, according to its definition, several factors are commonly considered in the Western context,

* Corresponding author.
E-mail addresses: liwenyue1991@foxmail.com (W. Li), ylong@tsinghua.edu.cn (Y. Long), mpk654@gmail.com (M.-P. Kwan), liunr18@mails.tsinghua.edu.cn (N. Liu), yanli427@hotmail.com (Y. Li), 33848350@qq.com (Y. Zhang).

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including the presence of litter, abandoned cars, and poor building maintenance (Raudenbush & Sampson, 1999). NPD is often assessed based on these elements and on residents' perceptions along with other objective characteristics. For methods used that rely on residents' perceptions, questionnaires or interviews were distributed to collect the data (Gold & Nepomnyaschy, 2018; Buil-Gil et al., 2019). The results are likely influenced by people's preferences and backgrounds (Latkin et al., 2009). For methods that rely on objective characteristics, NPD was originally assessed through systematic neighborhood audits, wherein trained raters record the characteristics of street segments according to formal procedures (Reiss, 1971). In the earlier stage, raters would travel to the site to conduct the audit. However, with the increasing availability of street view images, researchers can conduct virtual audits of neighborhoods by capturing street view images such as those from Google Street View (Carson & Janssen, 2012; Mooney et al., 2017; Quinn et al., 2016). In recent studies, artificial intelligence methods have been applied to automatically audit certain physical disorder characteristics for large-scale street view images (Javanmardi et al., 2020; Keralis et al., 2020).

To assess exposure to NPD, the spatial extents in previous studies are usually small geographic units such as census blocks or administrative units. Some studies accept that the built environment characteristics around where the individuals live are what they are exposed to, which can be classified as a static residence-based approach (Auler et al., 2020; Pai & Kim, 2017; Buil-Gil et al., 2019). The static residence-based approach may have disadvantages. First, the research findings on the impact of area-based attributes on individual behaviors could be affected by how the residential units are geographically delineated (Kwan, 2012), which is referred to as the uncertain geographic context problem (UGCoP). Second, the assessment of individual exposure to mobility-dependent environmental factors can be erroneous when mobility needs are ignored as individuals' daily movement may amplify or attenuate the exposures they experienced in their residential neighborhoods (Kwan, 2018b). This is referred to as the neighborhood effect averaging problem (NEAP). An important way to avoid the UGCoP and the NEAP is to consider individuals' mobility in exposure assessments (Kwan, 2012; Kwan, 2018a, b). Moreover, according to the above pathways that illustrate that the built environment affects health, only the built-environment characteristics people interact with can influence their health outcomes. However, to the best of our knowledge, no study about exposure to NPD has used the mobility-based approach. Therefore, a new approach that considers individuals' spatiotemporal mobility with a reasonable cost is urgently needed.

In recent years, street view images have become the most commonly used data for assessment of exposure to NPD. However, the reliability of street view image auditing largely depends on its areal coverage and update frequency. Meanwhile, with the development of sensor technology, a variety of wearable devices have been developed. Among them, wearable cameras are light, small, and portable enough to be carried by individuals and record the graphic characteristics of the built environment they are exposed to, including NPD items. Wearable cameras have already been employed to monitor people's exposure to smoking (Gurtner et al., 2019), alcohol (Chambers et al., 2017a, 2018, 2019), $PM_{2.5}$ (Salmon et al., 2018), UV radiation (Kurz et al., 2020), neighborhood (Chambers, Pearson, Kawachi, et al., 2017) and greenery (Zhang et al., 2020). However, there has been no research to date on using wearable cameras to assess individual exposure to NPD or built-environment characteristics.

In this paper, we proposed a mobility-based approach to assess individual exposure to NPD using wearable cameras. We compared the proposed new approach with the static residence-based approach and other alternative mobility-based approaches using street view images to demonstrate its effectiveness. A one-week study with four volunteers was conducted. Based on this study, we described how the approach was implemented and why we proposed the approach.

2. Methods

This paper proposed an approach for assessing individual exposure to NPD. The methodology consists of the following three components.

1) Four volunteers were invited to carry out a one-week experiment that assessed their exposure to NPD; volunteers were equipped with wearable cameras, and were asked about their daily travel routes;
2) Individual exposure to NPD was assessed by auditing the pictures taken by the wearable cameras, visualizing the one-week lifelogging of exposure to NPD, and calculating the average exposure, cumulative exposure, and peak exposure to NPD;
3) The effectiveness of our proposed approach was validated by comparing the results with those obtained through other approaches, specifically a static residence-based approach and mobility-based approaches using street view images.

The first two components focus on assessing exposure to NPD by the mobility-based approach using wearable cameras, and the third focuses on addressing why we proposed the above approach to conduct the assessment.

2.1. The volunteers, wearable cameras, and procedures of the experiment

In Beijing, we recruited four volunteers from different backgrounds to participate in a one-week study. The volunteers included an 84-year-old retired professor, a 23-year-old college student, a 24-year-old office worker, and a 27-year-old homeworker who works from home. The volunteers represent different lifestyles with different activity spaces, activity durations, and travel modes. Because this research focuses on methodological innovation, a small number of volunteers with representativeness is enough to propose a new method. Wearable cameras were then used to collect data on each volunteer's exposure to NPD. The wearable camera we used in this study was Narrative Clip 2, which meets the requirements of our experiment for its small size and light weight. Its battery can support 12–15 h of recording with a full charge, so its long battery life also meets the requirements. In our setting, Narrative Clip 2 takes a picture every 30 s, which means it has a relatively high temporal resolution in recording the volunteers' exposure to the environment.

Our experiment was carried out from August to October 2018. Specifically, each volunteer was asked to securely outfit a wearable camera on the collar to capture the front view during the daytime over a whole week. As a routine, every morning at approximately 8 a.m. after awaking and washing up, the volunteers would wear the cameras on their collars and make sure the lens is stable, forward, unobscured, and the batteries are fully charged. During the wearing period, the volunteers would ensure that the wearable cameras were working correctly unless they were engaging in an activity or event that was not suitable for taking pictures. Then, every evening from approximately 7 p.m.–11 p.m. before preparing for bed, the volunteers were able to take off the wearable cameras and export the pictures to our mobile hard disc drives by computer. For privacy reasons, the volunteers could remove or hide the camera anytime they wanted and could delete the pictures with private information before submission. In addition, every night, the volunteers were asked to complete an online questionnaire to report their travels during that day by checking the pictures and through memory recall after which they drew their routes on a map. The records of their travels were divided into routes and stops. For routes, when volunteers walked from indoor space to outdoor space, switched their vehicles (e.g., from a bus to a bike), or changed from a stationary status (stop) to move, the end of a prior route was defined and a new route started. The records of each route included the starting position, ending location, and estimated duration, as well as the travel mode. For stops, if the volunteers stayed in the same place for more than 2 min, it was defined as a stop. The records of each stop included the stop location and stop duration.

2.2. Assessment of exposure to NPD

The checklist of NPD factors was designed according to the assessment framework in previous studies (Quinn et al., 2016; Sampson & Raudenbush, 1999) and derived from typical street environment problems in Beijing, including 5 categories and 19 items (Chen & Long, 2021). The first category of the checklist was architectural items, which included abandoned buildings, buildings with damaged structures, buildings with damaged facades, buildings with unkempt facades, graffiti/illegal advertisement, and illegal/temporary buildings. The second category was comprised of commercial items, including stores with poor signboards, stores with poor facades, street vending, vacant and pending stores. The third category contained environmental items, including messy and unmaintained greenery, garbage/litter on the street, abandoned vehicles, and construction fence remnants. The fourth category covered road items, such as unpaved roads, broken roads, and roads stacked with private belongings. The last category related to other infrastructure items, including broken infrastructures and damaged public interfaces. We weighted the 19 NPD factors according to their impact on health (see Appendix A).

We assessed the volunteers' exposure to NPD by manually auditing the pictures taken by the wearable cameras during our experiment. We compared manual auditing with artificial intelligence auditing; due to the lower accuracy of the latter, we ultimately chose the manual auditing method. An auditor with a professional background in architecture was hired to audit all pictures on an online browser-based assessment platform we developed (Fig. 1). The assessment platform included two parts on the graphic interface: on the left is a picture taken by a wearable camera, and on the right is a checklist including the 19 NPD items in 5 categories. For each picture, the auditor was required to choose the NPD items in the checklist that were reflected in the picture. Then, the platform will label the weight of the item if an item was chosen; otherwise, the label was "0". The assessment results for each picture were the sum of the labels for each item, as shown in Equation (1), and the results were between 0 and 100.

$$PD_{j,k} = \sum_{i=1}^{19} PD_{i,j,k} \tag{1}$$

where $\boldsymbol{PD}$ is the NPD assessment result of a picture, $\boldsymbol{i}$ is the serial number of the NPD assessment item, $\boldsymbol{j}$ is the rank of the pictures, and $\boldsymbol{k}$ is the rank of the volunteer.

Then, for each volunteer, we assessed their daily or weekly exposure to NPD by calculating three exposure indicators commonly used in existing studies. The first indicator is average exposure, which is the average value of NPD of the pictures, as shown in Equation (2). It reflects the average characteristics of the environment to which they were exposed. The second indicator is peak exposure, which is the maximum value of NPD assessment, as shown in Equation (3). It reflects the worst characteristic of the environment to which they were exposed. The third

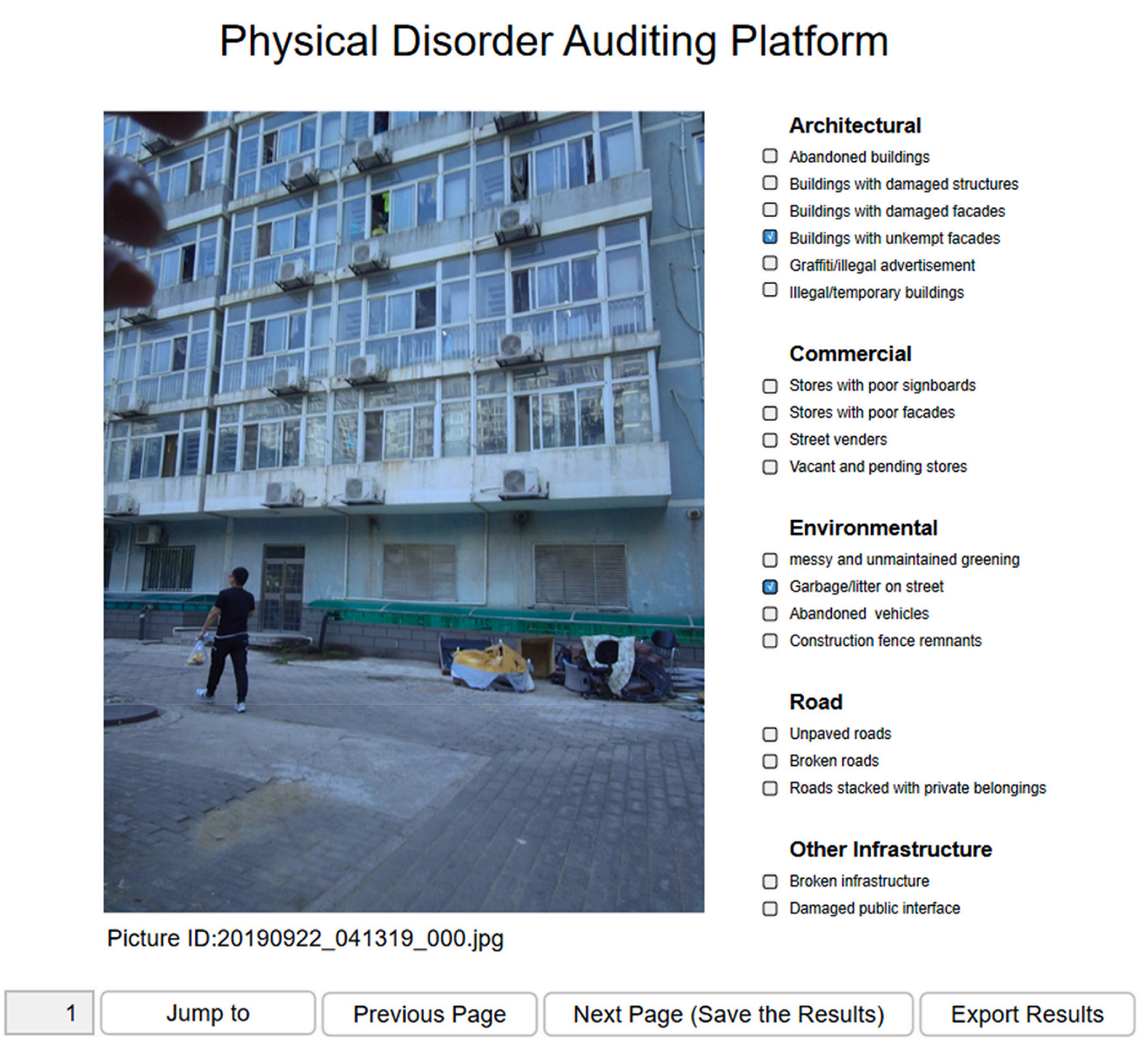

Fig. 1. Online browser-based assessment platform for NPD.

indicator is cumulative exposure, which is the time-weighted sum value of NPD assessment calculated in hours, by which the exposure time for each picture was regarded as 30 s because the wearable cameras took pictures at 30 s intervals in this study, as shown in Equation (4). It reflects the time accumulated characteristics of the environment to which the volunteers were exposed.

$$AE_k = \frac{\sum_{j=1}^{n} PD_{j,k}}{n} \quad (2)$$

$$PE_k = \max_j PD_{j,k} \quad (3)$$

$$CE_k = \sum_{j=1}^{n} PD_{j,k}\Delta t \quad (4)$$

where AE_k, PE_k, CE_k, are the average exposure, peak exposure, and cumulative exposure for volunteer k respectively. n is the total number of valid pictures for each volunteer for the week (weekly results) or for the day (daily results). Δt is the exposure time for each picture (i.e., 30 s, which was converted into hours).

2.3. Comparison with other exposure assessment approaches

To verify the effectiveness of our proposed approach, we compared its results with those obtained by other approaches. The static residence-

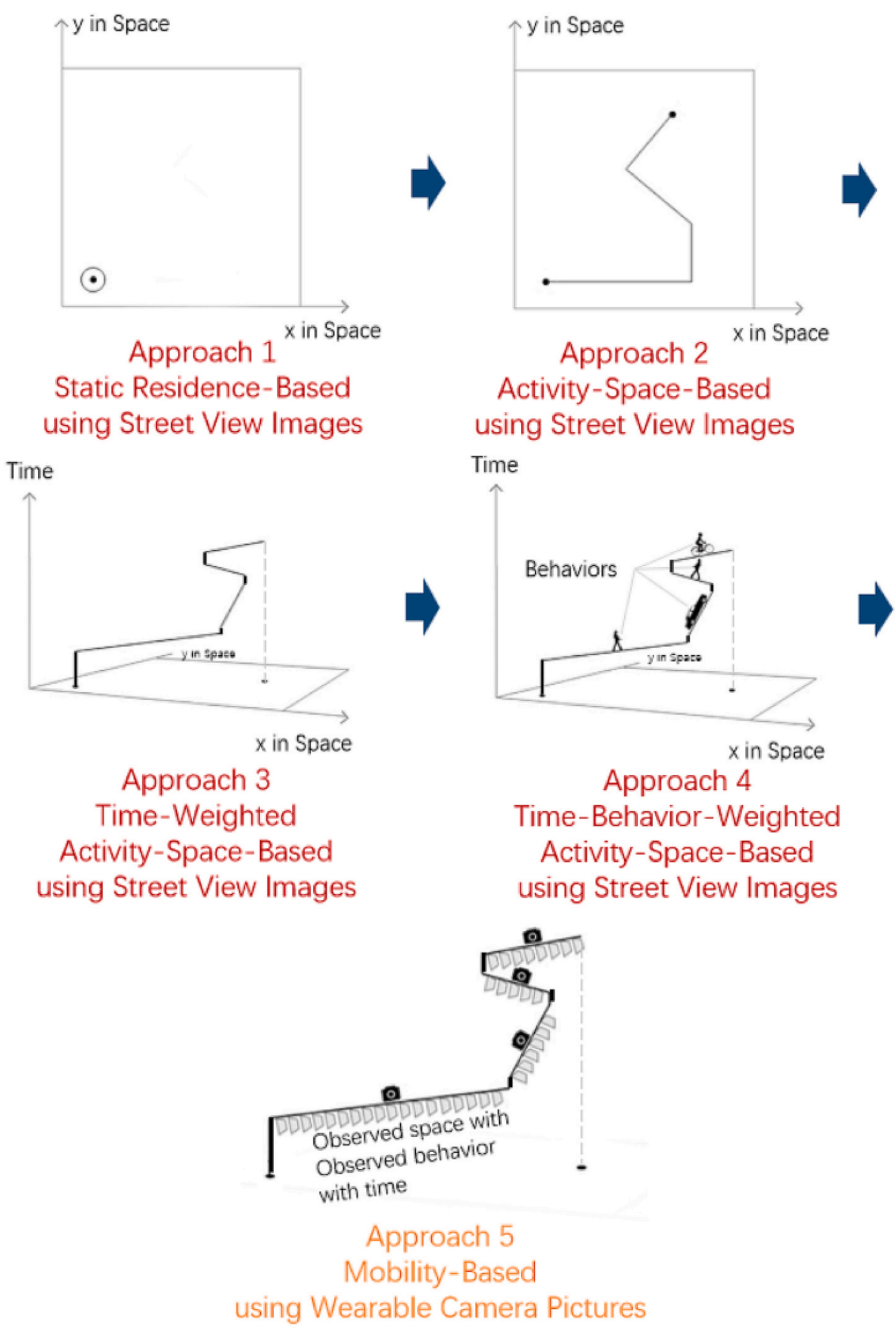

Fig. 2. Diagram for assessment approaches of exposure to NPD.

based approach and three alternative mobility-based approaches were numbered as **Approaches 1 to 4**, respectively, and the mobility-based approach using wearable camera pictures we proposed was numbered as **Approach 5** (as shown in Fig. 2). Approaches 1 to 4 are listed by the method of exhaustion, combining the commonly used street view image data with existing assessment theories. Please find the details for data processing of Approaches 1 to 4 in Appendix B.

The static residence-based approach assumes that people are relatively static at their residential place, so they regard the environmental characteristics around their residence as the environment to which they are exposed. In previous studies, buffer areas, census blocks, and administrative units around people's homes were often used to delineate the assessment area (Kwan, 2012). In this article, we use the buffer area as the spatial extent and include the static residence-based approach to assessing NPD by street view images as follows.

Approach 1 – Static Residence-Based Approach: We took the location of the volunteers' house as the center and used a circular buffer area with a commonly used radius of 500 m (Chambers et al., 2017b; Larsen et al., 2009) as the assessment area of exposure to NPD.

In past studies, mobility-based approaches were implemented by overlaying people's spatial-temporal trajectories with a map of environmental characteristics, which were simulated by interpolating environmental monitoring data from monitoring stations or by environmental characteristics calculated by zonal units from GIS data (Park & Kwan, 2017; Smith et al., 2021; Yi et al., 2019). Such approaches have been used in exposure assessment already, although still not in exposure to NPD. In this article, because NPD can be objectively captured by street view images, overlaying people's space-time trajectories or some characteristics of their travel behaviors with environmental characteristics simulated by street view images can also be a method for implementing the mobility-based approach. Based on existing studies, the characteristics of people's travel behaviors include activity space, travel duration (time taken to get from one location to another and spent at a particular location), and the travel mode. Based on the different considerations of the above travel behaviors, three alternative mobility-based approaches using street view images are included. These are the Activity-Space-Based Approach, Time-Weighted Activity-Space-Based Approach, and Time-Behavior-Weighted Activity-Space-Based Approach.

Approach 2 – Activity-Space-Based Approach: We regarded the activity space as the contextual area to examine people's environmental exposure.

Approach 3 – Time-Weighted Activity-Space-Based Approach: Based on Approach 2, we regarded the activity space as the contextual area and considered the duration at each location to examine individual environmental exposures.

Approach 4 – Time-Behavior-Weighted Activity-Space-Based Approach: Based on Approach 3, we noticed that the modes of travel also influence perceived NPD, so we further took it into consideration by assigning different weights to different travel modes, on the basis of consideration of activity space and travel time. The weights of the travel modes were determined by the scope of the built environment, where the details are described in Appendix B.

We then compared the evaluation results of Approaches 1 to 4 with those of Approach 5 by conducting two-tailed paired sample *t*-tests. The *t*-test was used to test if there was a significant difference between the mean values of the two groups. For each comparison, each volunteer's daily exposure assessment results calculated as the average exposure, peak exposure, and cumulative exposure were then compared by *t*-tests. By using *t*-tests, we seek to demonstrate that Approaches 1 to 4 are significantly different from Approach 5; thus, Approach 5 cannot be replaced. We performed further comparisons between Approach 1 and Approaches 2 to 4 to identify whether the consideration of mobility leads to different results and between Approach 4 and Approach 5 to identify whether the use of wearable cameras leads to different results. As Approaches 4 and 5 are both mobility-based assessments with consideration of activity space, travel duration, and travel mode, they are closest in assessment theory because they both consider mobility and differ only in using street view images or wearable camera pictures. Thus, Approaches 4 and 5 can be considered comparable. To further explain the mechanism of the difference, we also compared the detailed assessment results of Approach 4 and Approach 5 through a case study.

3. Results

3.1. Overall results of the experimental data collection

In our experiment, a total of 22,442 pictures were taken by Narrative Clip 2, among which 2,874 pictures were taken in outdoor spaces, with the remaining taken in indoor spaces. As NPD refers to the dilapidation of the outdoor built environment, we only consider the outdoor pictures in the analysis. The number of outdoor pictures collected each day is shown in Table 1. For the space-time mobility questionnaire, 118 routes and 27 stops (as shown in Fig. 3, Table 2) were recorded. During the experiment, most activities of the four volunteers took place near where they live and work, except that the homeworker took a short trip to the suburbs, and the retired professor attended a party far from her home by bus. For all four persons, walking and riding a bike/electric bike are the most commonly used travel modes.

3.2. Assessment results based on pictures of the wearable cameras

3.2.1. NPD assessment results

The checklist of NPD assessment includes 19 items, and the theoretical NPD score of each picture is 0–100, but the actual assessment values ranged from 0 to 19.92 because NDP items seldom appear together. In our experiment, the four most frequently appeared NPD

Table 1
Number of days and pictures collected in the experiment.

Occupation	Date in 2018	Participation or Not	Number of Outdoor Pictures
College student	Sep 22	Data available	307
	Sep 23	Data available	126
	Sep 24	Data available	49
	Sep 25	Data available	35
	Sep 26	Data available	148
	Sep 27	Unable to recall the routes, data not included	0
	Sep 28	Unable to recall the routes, data not included	0
Homeworker	Sep 23	Data available	196
	Sep 24	Data available	210
	Sep 25	Stay at home, data not included	0
	Sep 26	Data available	174
	Sep 27	Data available	202
	Sep 28	Data available	242
	Sep 29	Data available	69
Office worker	Oct 05	Data available	132
	Oct 06	Data available	74
	Oct 09	Data available	34
	Oct 10	Unable to recall the routes, data not included	0
	Sep 16	Data available	267
	Sep 18	Data available	65
	Sep 19	Data available	96
Retired professor	Sep 22	Data available	18
	Sep 23	Data available	20
	Sep 24	Data available	307
	Sep 25	Stay at home, data not included	0
	Sep 26	Data available	71
	Sep 27	Data available	20
	Sep 28	Data available	12

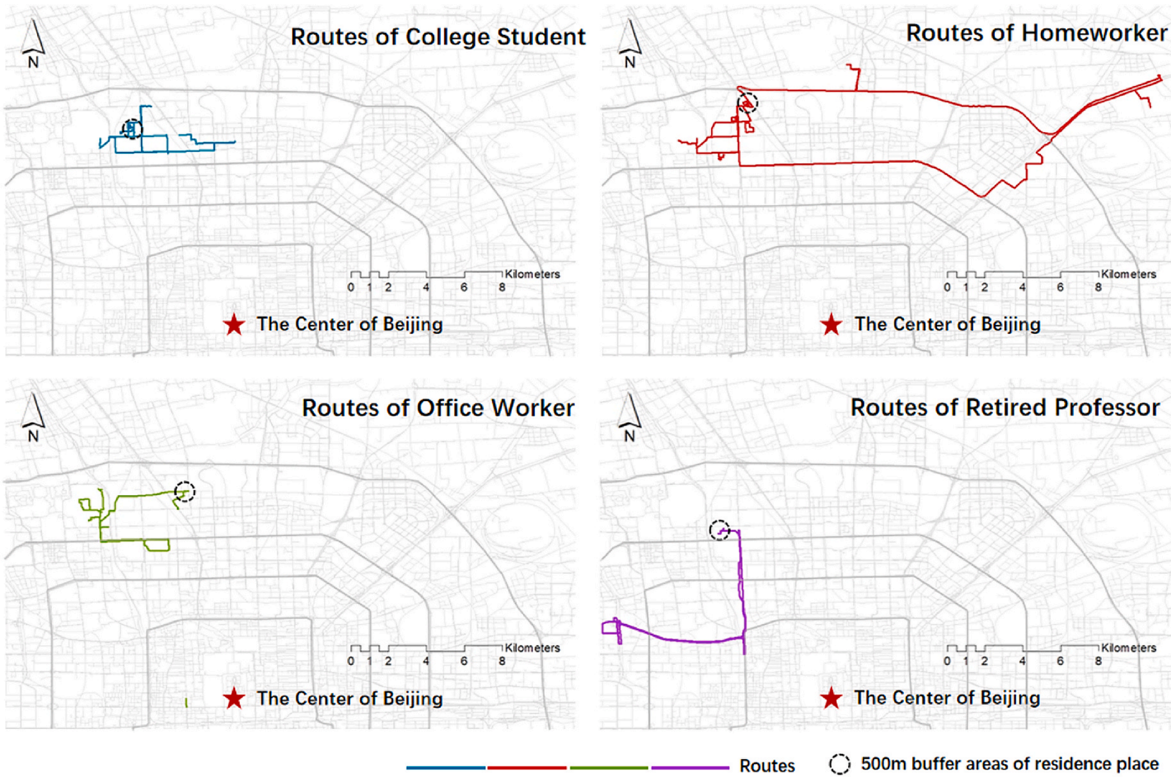

Fig. 3. Routes and buffer areas of residence of volunteers.

Table 2
Number of routes and stops we collected in the experiment.

	Routes					Stops
	Total	By walk	By bike/ electric bike	By taking someone else's electric bike[a]	By car or bus	
College Student	30	15	7	8	0	4
Homeworker	32	20	3	1	8	13
Office worker	40	18	19	0	3	4
Retired Professor	16	9	4	0	3	6
Total	118	62	33	9	14	27

[a] "By bike/electric bike" means the volunteer was riding a bike or electric bike, while "By taking someone else's electric bike" means the volunteer was sitting on an electric bike someone else is riding.

items were the following: roads stacked with private belongings appeared 301 times, messy and unmaintained greenery appeared 209 times, broken infrastructures appeared 205 times, broken roads appeared 116 times, and other items appeared no more than 50 times. In total, 27.14% of the pictures had NPD items. The average NPD score for all the outdoor pictures is 1.60, with 2,094 pictures scored 0. Among pictures with NPD items, 708 pictures have 1 NPD item that appeared inside, 63 pictures have 2, 8 pictures have 3, and 1 picture has 4.

3.2.2. *One-week lifelogging of exposure to NPD for the volunteer*

We visualized the one-week lifelogging of exposure to NPD by taking the homeworker as an example, as shown in Fig. 4. Because the homeworker has the most outdoor pictures and her travel modes cover all five types, the one-week lifelogging of the homeworker is typical for visualization and analysis.

The lifelogging of NPD can be summarized into higher and lower exposure patterns, which are influenced by travel modes. In the higher exposure pattern, the homeworker moved by walking or riding a bike/electric bike, so she had high or frequent exposure to NPD. In the lower exposure pattern, the homeworker moved by riding a bike/electric bike, taking a bus or a car, which leads to limited interaction with the built environment and, thus, low or infrequent exposure to NPD. Details of the typical case of higher and lower exposure patterns are described in Appendix C.

The above results indicate that the levels of exposure to NPD under different travel modes were quite different, and wearable cameras can capture the differences. Thus, individual exposure to NPD is influenced by both the objective NPD characteristic of the environment and people's travel behavior, where the latter includes the activity space, travel duration, and travel modes. In existing studies, some of the exposure assessments have applied the mobility-based approach by considering people's activity space and travel duration, but few considered or emphasized the influence of travel modes. Our analysis showed that travel modes also matter, which means that even if there were elements of NPD in the built environment, people may not perceive it when they encountered them because of the restriction of the travel mode. As wearable cameras are worn by volunteers and they take pictures in succession, the pictures can well reflect NPD exposure under the influence of travel behavior.

3.2.3. *Average, peak, and cumulative exposure of NPD*

Based on the NPD assessment results from images collected by wearable cameras through manual audits, we calculated three exposure indicators for each volunteer, namely, the average exposure, peak exposure, and cumulative exposure, as shown in Fig. 5. The different results of the four volunteers reflect different lifestyles and living environments.

In consideration of mobility, the assessment of NPD can be enriched by calculating the three indicators. These indicators reflect the exposure results from different dimensions, and together they can comprehensively assess the results of exposure to NPD. Considering that individuals have different lifestyles and daily environments, the three indicators are

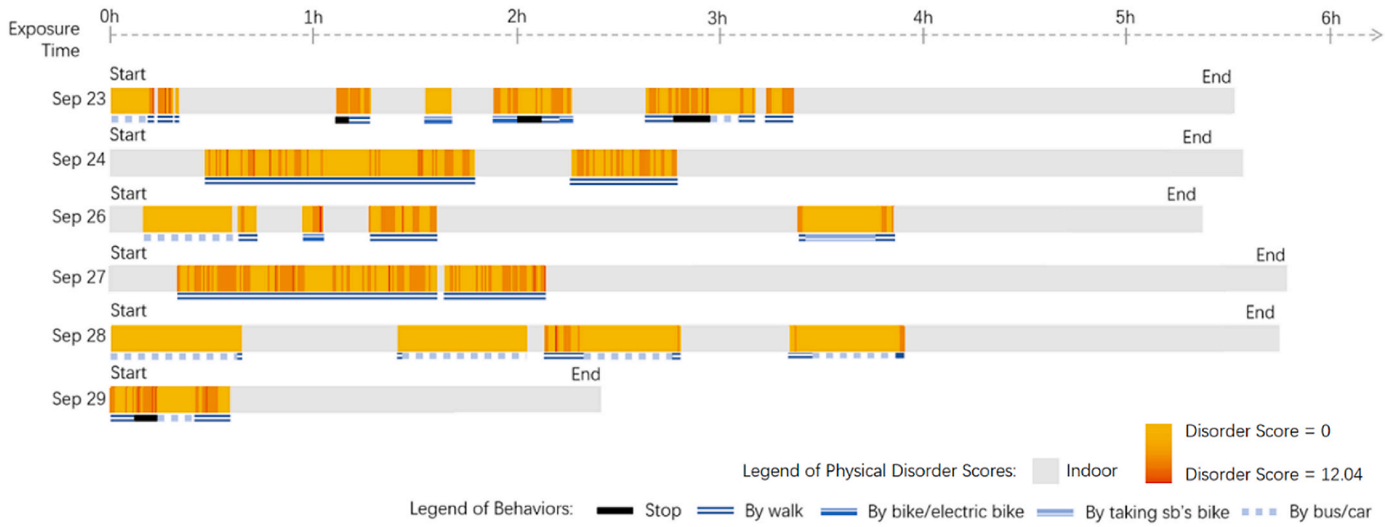

Fig. 4. Exposure to NPD one-week lifelogging of the homeworker during the experiment.

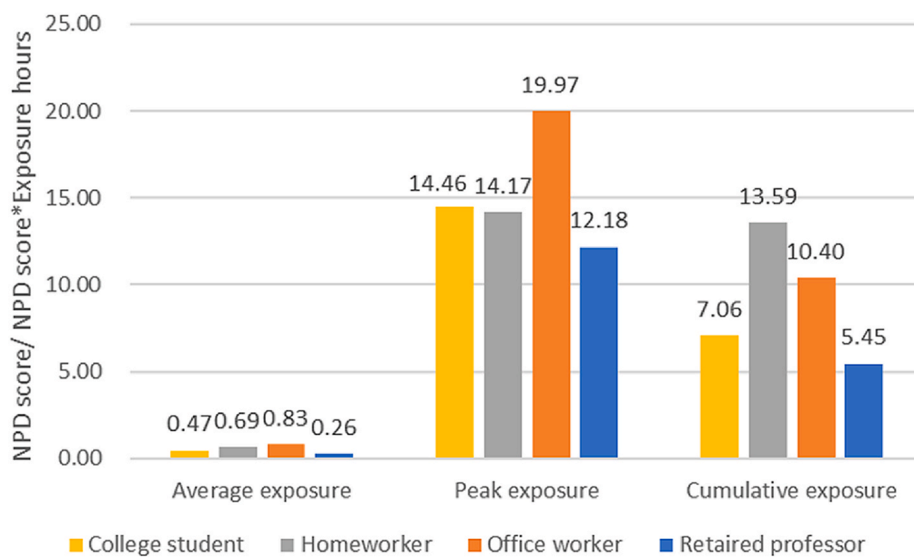

Fig. 5. Weekly evaluation of exposure to NPD by wearable cameras.

all necessary to reveal the exposure characteristics. The indicators can also be used in future research on the association between NPD and health, and the corresponding indicators can be used according to the demand.

3.3. Comparison of assessment by wearable cameras

3.3.1. Comparison of the overall results with other assessment approaches

To demonstrate that the mobility-based approach to assessing individual exposure to NPD using wearable cameras was essential, we compared the daily assessment results for each volunteer with other alternative approaches by *t*-test.

The results in Table 3 show that for some volunteers and for some indicators, the results of exposure to NPD assessed by Approaches 1 to 4 may be significantly different from those obtained by Approach 5, suggesting that Approaches 1 to 4 could not replace Approach 5. Then, we further demonstrate how taking mobility into account and the use of wearable cameras may lead to different results. On the one hand, in Table 4, the results also indicate that for some people and some indicators, there are significant differences between Approach 1 and Approaches 2 to 4, which means that the necessity for the consideration of mobility matters. On the other hand, in Table 3, the *t*-test results show that assessments by Approach 4 and Approach 5 are also significantly different, which means that using wearable cameras also led to different results. Detailed results of Approaches 1 to 4 and their comparisons with Approach 5 are visualized and described in Appendix D.

3.3.2. Explanation of the different results with other assessment approaches

Previous studies have discussed that because of UGCoP (Kwan, 2012) and NEAP (Kwan, 2018b), different definitions of neighborhood areas and different degrees of mobility considerations may lead to higher or lower exposure assessment results, which explains why the different approaches produce different results. Previous studies have also discussed that consideration of mobility in exposure assessments would generate more accurate results (Kim & Kwan, 2021; Kwan, 2012, 2018a, b), which suggests that Approach 2 to 4 are more accurate than Approach 1 when the results are significantly different.

Moreover, to further explore why the street view images led to different assessment results and identify which type of data produced more accurate results, we further analyzed the detailed assessment results of Approaches 4 and 5 by taking the weekly lifelogging of the homeworker on September 24 as an example and comparing the

Table 3
p value of two-tailed paired *t*-test of daily exposure to NPD, approach 5 as the benchmark.

Index	Volunteer	Approach 1 & 5#	Approach 2 & 5#	Approach 3 & 5#	Approach 4 & 5#
Average Exposure	Retired Professor	0.1178	0.9508	0.6340	0.4361
	College Student	0.2715	0.6716	0.3701	0.2213
	Office worker	0.0149*	0.2121	0.0270*	0.0093**
	Homeworker	0.1652	0.0121*	0.0114*	0.0041**
Peak Exposure	Retired Professor	0.0004**	0.0119*	0.0119	0.0062**
	College Student	0.0243*	0.5990	0.5990	0.1713
	Office worker	0.0445*	0.0549	0.0549	0.0227*
	Homeworker	0.1771	0.1771	0.1771	0.2321
Cumulative Exposure	Retired Professor	0.0000**	0.0091**	0.9956	0.5508
	College Student	0.0000**	0.0125*	0.2984	0.2331
	Office worker	0.0000**	0.0221*	0.0316*	0.0253*
	Homeworker	0.0000**	0.0110*	0.0545	0.0150*

**$p < 0.01$, *$p < 0.05$.
Approach 1, Static Residence-Based Approach; Approach 2, Activity-Space-Based Approach; Approach 3, Time-Weighted Activity-Space-Based Approach; Approach 4, Time-Behavior-Weighted Activity-Space-Based Approach; Approach 5, Mobility-Based Approach.

Table 4
p value of two-tailed paired *t*-test of daily exposure to NPD, approach 1 as the benchmark.

Index	Volunteer	Approach 1 & 2#	Approach 1 & 3#	Approach 1 & 4#
Average Exposure	Retired Professor	0.1566	0.0766	0.1760
	College Student	0.0298*	0.0023*	0.0016**
	Office worker	0.6028	0.2312	0.0123*
	Homeworker	0.0091**	0.0007**	0.0000**
Peak Exposure	Retired Professor	0.0000**	0.0000**	0.0000**
	College Student	0.0107*	0.0107**	0.0007**
	Office worker	0.9276	0.9276	0.1582
	Homeworker	–	–	0.0103*
Cumulative Exposure	Retired Professor	0.1566	0.0000**	0.0000**
	College Student	0.0298*	0.0000**	0.0000**
	Office worker	0.6028	0.0000**	0.0000**
	Homeworker	0.0091**	0.0000**	0.0000**

**$p < 0.01$, *$p < 0.05$.
Approach 1, Static Residence-Based Approach; Approach 2, Activity-Space-Based Approach; Approach 3, Time-Weighted Activity-Space-Based Approach; Approach 4, Time-Behavior-Weighted Activity-Space-Based Approach.
- The NPD exposure scores for all six days are the same and no *t*-test can be conducted.

exposure to NPD of the two approaches in two identical places, as shown in Fig. 6. Approaches 4 and 5 are similar in assessment theory because they are both mobility-based approaches with full consideration of travel behavior, but they are different in the data collection method, which is by street view images and by pictures captured by wearable cameras, respectively.

The comparison results showed that the street view images from Baidu Maps were outdated, and their coverage was incomplete, which means that using street view images cannot accurately assess the real exposure. For example, in place ①, the pictures captured by the wearable cameras showed that the streets and buildings have been recently repaired, but the images from the street view showed that the streets and the buildings were all under construction, with broken roads and messy greenery. Another example is in place ②, where there were no street view images recorded on the Baidu Map, but the wearable cameras can take pictures to record the environmental exposure normally. Thus, the assessment results by wearable cameras collect more NPD items than those by street view images in our experiment, but they are closer to the actual conditions. All comparisons above show the advantages of assessing exposure by wearable cameras because they comprehensively reflect the built environment that people actually see, which street view images cannot.

In addition to differences in the accuracy of the results, the differences between Approach 4 and Approach 5 are also due to the difference in convenience because obtaining the results by Approach 4 requires much more work. For Approach 4, we need the data of both the individuals' travel behavior and the data of the characteristics of the built environment, so the experimental data included the travel information obtained by questionnaire and the street view images downloaded from Baidu Map. In our experiment, also for Approach 4, the pictures taken by wearable cameras might also be used for the volunteers as an auxiliary tool for timing when recalling their activities and travels. As the data in Approach 4 were from multiple sources, it took a lot of work to overlay the street view image data and the travel routes. However, for Approach 5, auditing the pictures of the wearable cameras was enough for the assessment, and there was only one data source and less processing.

The comparison shows that the Static Residence-Based Approach, the Activity-Space-Based Approach, the Time-Weighted Activity-Space-Based Approach, and the Time-Behavior-Weighted Activity-Space-Based Approach cannot assess individual exposure to physical exposure accurately and conveniently, further highlighting the importance of using wearable cameras to record NPD exposure through the mobility-based approach.

4. Discussion

4.1. Academic contributions

This paper is innovative in two aspects. First, for the assessment theory, the mobility-based approach was applied in assessing individual exposure to NPD. Second, for the assessment tool, wearable cameras instead of street view maps were used to collect the imagery data for evaluating the NPD items to which people were exposed. With the proposed approach, we can accurately and conveniently assess individual exposure to NPD, while in existing studies, the commonly used assessment approach has a large degree of estimation. To the best of our knowledge, this study is the first to assess individual exposure to NPD (or other built-environment characteristics) by using wearable cameras. We would like to emphasize for other researchers the importance of accurate assessment of individual exposure to NPD. Further studies on the relationship between NPD and health outcomes should consider our assessment approach as accurate assessment can provide solid evidence as to how NPD may impact health outcomes.

4.2. Comparison with literature

Zhang et al. (2020) used the wearable camera to assess exposure to urban greenery, which can be seen as using a similar method as this study to learn the exposure of a different outdoor environmental element. In Zhang's study, the authors compared the wearable camera-based approach with person recall and found that the wearable camera-based approach recorded more details, while personal recall tended to overestimate or underestimate the exposure. However, the method based on personal recall is of course too old and too rough, and the comparison of this study is not solid enough. In our study, more approaches are compared with the wearable camera-based approach, including not only the commonly used approach (Approach 1) but also some newly designed approaches (Approaches 2 to 4). By comparing the

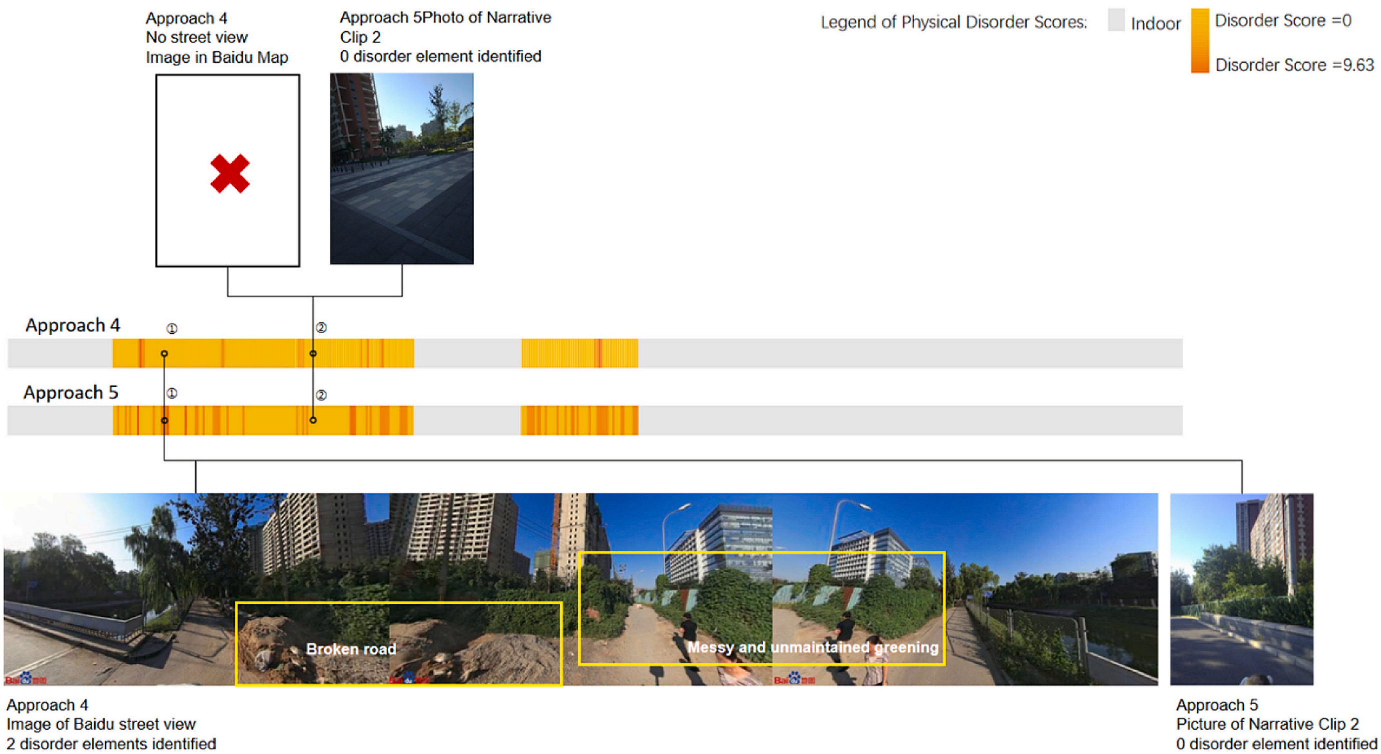

Fig. 6. Comparison of NPD assessment results between approach 4 and approach 5, taking day-long lifelogging of the homeworker on September 24 as an example.

assessment results of NPD exposure based on different approaches, the results lead to significantly different results and are more convincing than Zhang's study. Moreover, Zhang et al. (2020) found that greenery exposure during movement is far more frequent than that during standing by dividing exposure into static and dynamic exposure. In this paper, we further find that exposure under different travel modes causes different NPD exposure patterns by dividing the exposure while moving more specifically according to different travel modes. Through a more detailed exposure division, the findings of this paper go deeper than those of Zhang et al. (2020).

Chambers et al. (2017a, 2017b, 2018) used GPS and wearable cameras to measure children's exposure to alcohol in their residential neighborhoods. In Chamber's studies, the GPS was always combined with the wearable camera. The wearable cameras were used as tools to confirm the spatial accuracy of the GPS or to measure the exposure in indoor microscale spaces where GPS produces low-quality data. In our studies, the NPD exposure assessment approach by the wearable camera (Approach 5) did not combine with GPS or any data about routes. We demonstrate that only the use of wearable cameras, without GPS, can well assess individuals' exposure to NPD by comparing it with other approaches using route data (Approaches 2 to 4), which emphasizes the superiority of wearable cameras.

4.3. Limitations

While our approach has various merits, it has several limitations and needs improvement in the future. First, the pictures taken by wearable cameras involve a large amount of private personal information, so it may not be easy to recruit participants for this kind of study. Therefore, the study established a mechanism for protecting the privacy of volunteers. During the data collection period, automatically removing private information such as faces and license plate numbers that appeared in the pictures would be ideal in the future. Second, limited to the experimental cost, we experimented with a very small sample size. Although it is enough to demonstrate the innovation of the method, revealing the effects of NPD exposure on health and finding population differences in NPD exposure still need a large sample experiment. Nevertheless, with the development of wearable devices, wearable cameras are increasingly affordable, and obtaining large sample exposure data using wearable cameras will become easier in the future. Third, as we take exposure to NPD as the assessment object, we only considered the characteristics of the outdoor environment in this study. However, people spent approximately 90% of their time indoors. The approach proposed in this paper can be further referenced to assess individual exposure to indoor environments because the characteristics of indoor environments cannot be known by using common open data such as street view images.

5. Conclusions

The innovation of this paper is to propose a new method of assessing individuals' NPD exposure, which is the mobility-based approach using wearable cameras. This is significant because by this method, we can conveniently consider the mobility of individuals and record the real-time true status of the built environment that individuals contact.

As previous studies on the assessment of NPD seldom focused on individual exposure, this paper proposed a mobility-based approach using wearable cameras to effectively assess individual exposure to NPD in the built environment and proposed three different exposure indicators to assess the exposure results: the average exposure, the peak exposure, and the cumulative exposure. Based on an experiment with four volunteers, we demonstrated how to apply the proposed approach to assess NPD. In this experiment, we found that individual exposure to NPD is influenced by both the objective characteristics of the built environment and individuals' travel behavior (both routes and modes), and by using wearable cameras with the three indicators, we can comprehensively assess the exposure from different dimensions with consideration of travel behavior. We compared the proposed approach with four alternative approaches using street view images. The comparisons showed that the assessments of individual exposure to NPD obtained by different approaches and by the proposed approach might be significantly different, even when the approaches that used street view images have considered the volunteers' activity spaces, travel durations, and travel modes. As street view images are generally out of date and incomplete in areal coverage, conducting the assessment by using wearable cameras is much more accurate. On the other hand, as assessing the NPD by street view images needs supporting data about the individual travel behavior from other sources, using wearable cameras has no such need, and the latter approach is more convenient. With the accurate and convenient assessment approach, we can better evaluate the health effects of exposure to NPD to provide more reliable evidence.

Author statement

All authors declare no conflict of interest.

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Appendix A

Weights of NPD Items

The NPD items have different degrees of impact on human health outcomes, so we regard the different NPD items to different degrees. To weight the NPD items we reviewed the relative references but there is no solid evidence for the comparable health impact degree of the NPD items. Reference to the (Gan et al., 2017), we sent a questionnaire to experts in fields of both the built environment and public health to scoring the items. For each item, we provided a text introduction and two pictures with the NPD item labeled in red boxes. Under each item, five degrees of discomfort were provided for the exports to choose from (from 0 to 4, 0 means feeling no discomfort and 4 means feeling very discomfort), representing the health impact of each item.

We received a total of 52 questionnaires, including 15 from experts in public health and 37 from experts in the built environment. There are three steps to calculate the weights of the NPD items. Firstly, for each questionnaire, we first normalized the discomfort scores for each NPD item. Secondly, for all the questionnaires, we calculated the average number of the normalized discomfort scores for each NPD item. Finally, we multiplied the average number of the discomfort score by 100 for NPD each item, to obtain the weights of the item. By the above calculation, the total weight of the 19 NPD items is 100, and the separate numbers of weights range from 4.68 to 7.14, as shown in Figure A1.

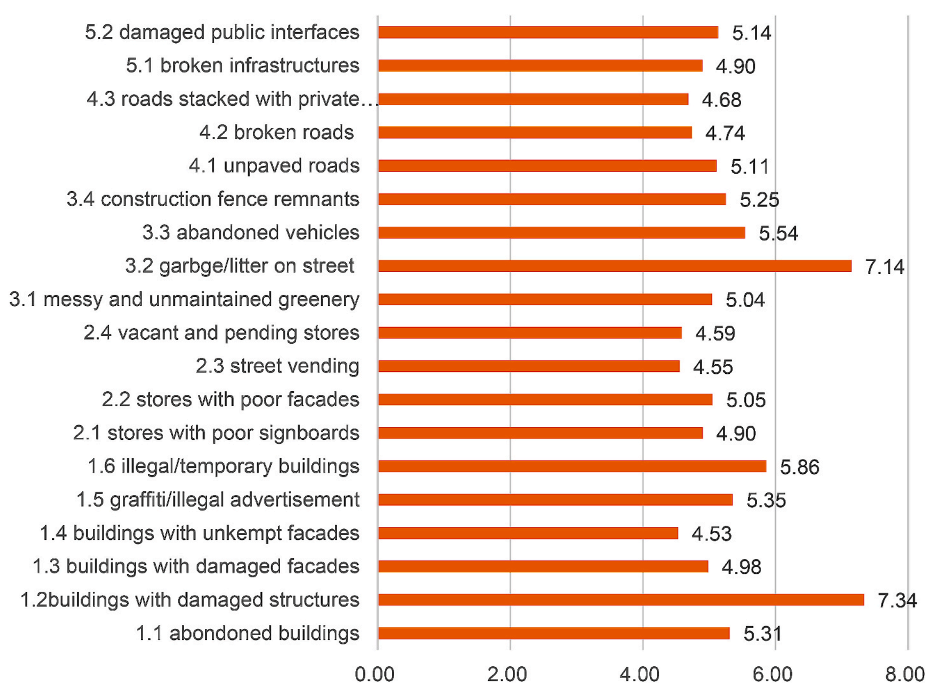

Fig. A.1. Weights of the NPD items

Appendix B

Method of Obtaining and Processing Street View Images For Approaches 1 to 4

To accurately obtain the street view images, through online street view map, we first checked the accuracy of routes and stops drawn by the volunteers by carefully matching the street view images and the wearable camera pictures. Specifically, we compared the street view image on each route with the wearable camera pictures taken at the same time to ensure that the route was correct. If the route could not match the wearable camera pictures, we corrected the route by searching for the location that appeared in wearable camera pictures. Then, we counted the number of wearable camera pictures on each route to evaluate the time spent on it as the wearable camera taken photos every 30 s.

With accurate routes and stops, here, we describe the method of obtaining and auditing street view images. According to the routes, for the streets on which the volunteers' wearable camera captured pictures, we divided them by vertices within a 50-m distance. For each vertex on routes and for each stop, we downloaded 4 street view images in the front, back, left and right directions from Baidu Map, whose street view images in Beijing perform better in the coverage area and update frequency than other products. We put the four images of the same vertex together into one, and then the NPD score was assessed vertex by vertex using the online-browser-based assessment platform. The auditor again reviewed the street view images from the street view according to the same checklist of NPD factors.

The details for data collection and data processing for Approaches 1 to 4 are listed in Table A1, and the results can also be assessed daily or weekly.

Table B.1
Data collection and data processing details for approaches 1 to 4

Approaches	Spatial Range of Data collection	Data processing
Approach 1 Static Residence-Based Approach	Street view images* from 500 m buffer areas near residential places	• The average exposure is the average NPD score of all the vertices in the buffer area of each volunteer's residence. • The peak exposure is the maximum score of all vertices in the buffer area of each volunteer's residence. • The cumulative exposure is the sum of the daily average exposure score multiplied by the number of exposure time, taking 24 h as the exposure time of a day.
Approach 2 Activity-Space-Based Approach	Street view images* from routes and stops**	• The average exposure is the average NPD score of the vertices along the routes and stops. • The peak exposure is the maximum NPD score of the vertices along the routes and stops. • The cumulative exposure is the sum of the daily average exposure score multiplied by the number of exposure times, taking 24 h as the exposure time of a day.
Approach 3 Time-Weighted Activity-Space-Based Approach	Street view images* from routes and stops**	• The average exposure is the time-weighted average of NPD scores for each street view vertex along the routes and stops, where the exposure duration of each street view vertex is from the questionnaire, calculated by averaging the exposure duration of each route or is the exposure duration of each stops. • The peak exposure is the maximum NPD score of the vertices along the routes and stops. • The cumulative exposure is the time-weighted sum of NPD scores for each street view vertex along the routes and stops.
Approach 4 Time-Behavior-Weighted Activity-Space-Based Approach	Street view images* from routes and stops**	• The average exposure is the time and travel mode*** weighted average of NPD scores for each street view vertex along the routes and stops. • The peak exposure is the travel mode*** weighted maximum NPD score of the vertices along the routes and stops. • The cumulative exposure is the time and travel mode*** weighted sum of NPD scores for each street view vertex along the routes and stops.

* Street view images are downloaded by Baidu Map, and downloading vertices are generated every 50 m along the roads.
** Only routes or stops in the outdoor urban space are considered.
*** Weights of travel modes:

We weighted the travel modes evenly from 0 to 1 based on the rank of peoples' contact with the built environment under these modes. The speed of movement and the field of view influence people's contact with the built environment. The slower people move, the more time they can spend experiencing NPD characteristics. The wilder view people have, the more area they can see to feel the NPD characteristics. The speed of these trips moving from slow to fast is ranked as follows: walking, riding a bike/electric bike and taking someone else's electric bike are tied in second place, and finally, by car or bus. The fields of these travel modes from wild to narrow are ranked as walking, riding bike/electric bike, taking someone else's electric bike, and car/bus tied last place.

Staying is weighted 1, as people always look around in the built environment;
By walk is weighted 0.8, as the speed is low and people may look left and right or just on the ground;
By bike/electric bike is weighted 0.6, as the speed is middle, and people have to look ahead;
By taking someone else's electric bike is weighted 0.4, as the speed is middle the cyclist may block the view of the passenger;
By car/bus is weighted 0.2, as the speed is fast and the car may block the view and people may not look outside.
Taking the subway as a weight of 0, no urban street space can be seen.

Appendix C

Typical Case of Higher and Lower Exposure Patterns

The typical cases for higher exposure patterns are during September 24 and September 27 (Fig. 4), when the homeworker's trips were made entirely by walking. On September 24, the homeworker had a walk on a nearby campus with her baby son, and the routes they passed by were mostly landscape trails or streets on campus with neat environments. Then, on September 27, she had a walk on other routes that mostly covered normal urban streets. The one-week lifelogging results showed that on September 24, the homeworker had high frequency but low severity of exposure to NPD, and on September 27, the exposure to NPD on that day was also frequent, but the proportion of high NPD score points was more than on September 24. The evaluation results are consistent with the actual situation, and the results show that for higher exposure patterns, the homeworker was sensitive to the NPD items in the outdoor environment.

The typical cases for lower exposure patterns are during September 28 and September 26 (Fig. 4). According to the questionnaires and the pictures, the homeworker took a private car for an outing in the suburbs of Beijing on September 28, and most of her outdoor time was spent in a car. Traveling by car can reduce the perceived NPD to a certain extent. Accordingly, when she was in the car, the contents of the pictures taken by the wearable camera were mostly the interior environment of the car, while the external built environment elements were partially obscured. Then, the homeworker had the least exposure to NPD. A similar phenomenon also occurred in the afternoon of September 26, when another person took the homeworker back home by using an electric bike. Because the homeworker sat too close to the cyclist (who rides the electric bike), the cyclist blocked the views of the homeworker's camera. Correspondingly, the back of the cyclist occupied most of the area of the pictures taken by the wearable camera. The one-week lifelogging shows that in the last third of the outdoor time, there was a long period in which the homeworker was not exposed to any NPD items. The evaluation results are also consistent with the actual scenario, and it shows that for lower exposure patterns, the homeworker was insensitive to the NPD items in the outdoor environment.

Appendix D

Weekly Assessment Results of Approach 1 to 5

We visualized the weekly assessment results of approaches 1 to 5 with bar charts, as shown in Figure B1, and further explained the differences between approaches 1 to 4 and 5.

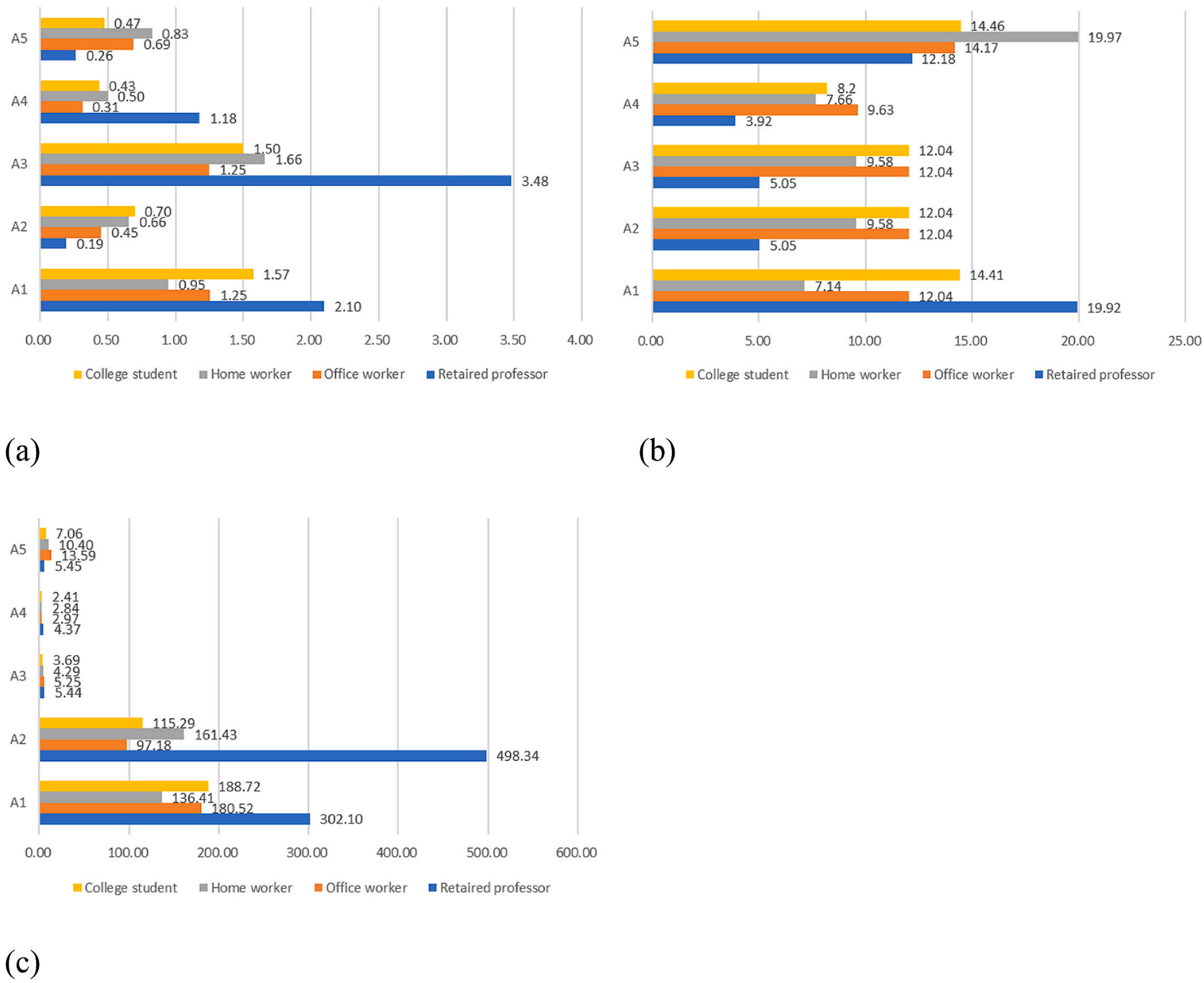

Fig. D.1. Overall evaluation of weekly exposure to NPD by (a) average exposure, (b) peak exposure, and (c) cumulative exposure

We compared the differences between Approach 1 and Approach 5 as follows. First, compared with Approach 5, the average exposure and peak exposure results of Approach 1, which is the static residence-based approach by street view image, were more or less underestimated or overestimated, consistent with what Kwan (2018a, b) discussed; thus, Approach 5 is better because it avoids the UGCoP and the NEAP. Second, the cumulative exposure scores of Approach 1 were significantly higher than those of Approach 5 for all four volunteers. As people spent most of their time indoors rather than outdoors, the real exposure duration was far less than 24 h and different every day; thus, Approach 5 by the wearable cameras was better because it can record the time people spent in every place.

Approaches 2 to 4 are all mobility-based approaches, and we compared their results with those of approach 5. In our experiment, Approaches 2 to 4, in turn, added the consideration of activity space, travel duration, and travel mode, and the assessment is, in turn, closer to Approach 5 in theory. However, for the assessment results of these approaches, deeper consideration of travel behavior did not lead to closer results to approach 5. The reason might be that the street view image cannot fully reflect the NPD items to which individuals are exposed because the street view images and the wearable camera pictures were taken at different times and from different perspectives.

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