Exploring built environment correlates of older adults' walking travel in real-time from lifelogging images: A pilot study of three neighbourhoods in Singapore

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Acknowledgements

This research is supported by the Singapore Ministry of National Development and the National Research Foundation, Prime Minister's Office under the Land and Liveability National Innovation Challenge (L2 NIC) Research Programme (L2 NIC Award No. L2NICTDF1-2017-2).

Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not reflect the views of the Singapore Ministry of National Development and National Research Foundation, Prime Minister's Office, Singapore.

We are deeply grateful to all research participants for generously giving their time and for sharing their personal experiences.

We duly acknowledge the following for their generous support and assistance: Dr Hyowon Lee who helped us select the lifelogging camera and provided technical assistance; Dr Ngai-Man Cheung who guided the development of image tagging software; research assistant Rochelle Chua who participated in data collection, cleaning and maintenance; student assistants Doan Thanh, You Song Shan and Jinjing Jiang who developed image tagging software, and student helpers who helped with data entry and image tagging.

Conflict of Interest

The authors have no conflict of interest to declare.

Funding

This material is based on research/work supported by Singapore’s Ministry of National Development and National Research Foundation under the Land and Liveability National Innovation Challenge Funding Programme (grant number L2NICTDF1-2017-2).

Ethics approval

The research protocol was approved by the Singapore University of Technology and Design Institutional Review Board.

Highlights

- This study uses a digital lifelogging methodology, passive photography
- We studied Singaporean older adults' walking trips from three study neighbourhoods
- Food courts and senior activity centres were frequently visited by pedestrians
- Features such as covered walkways and trees were related with pedestrian comfort
- Different groups of older adults have distinct walking habits and patterns

Exploring built environment correlates of older adults' walking travel from lifelogging images

Abstract

Utilising time-stamped lifelogging images collected from a sample of 30 older adults in three neighbourhoods of Singapore, this study explores older adults' daily walking travel patterns and their associations with neighbourhood-level built environment features. The visual lifelogging method uses a wearable camera to automatically record individual activities from a "first-person" perspective and capture novel information of environmental features encountered by individuals in real time. The findings reveal that older participants in the study areas, on average, take about 4 walking trips per day with an average trip length of about 15 minutes. Neighbourhood facilities including public open spaces, senior activity centres, and food courts are the most visited destinations while design features such as covered walkways, tree shades and street furniture are frequently encountered during walking trips.

Keywords

Visual lifelogging; Built environment; Walking travel; Older adults; Singapore

1. Introduction

Walking is an effective, convenient and environmental-friendly way of travel that is accessible to most people. It is increasingly recognised as a promising means of achieving regular physical activity, and reducing the risks of obesity and chronic diseases such as heart diseases, diabetes, high blood pressure, stroke, and cancer (Cunningham & Michael, 2004; Nelson et al., 2007). For older adults, walking can contribute substantially to active and healthy ageing (Barnett, Barnett, Nathan, Van Cauwenberg, & Cerin, 2017).

Many empirical studies have explored the effects of the built environment on individual walking travel. Previous findings indicate that various neighbourhood land use and design features, such as high density, land use mix, proximity to destinations (public transit hubs, parks, shops), good street connectivity and design, tend to encourage walking (Sallis, Frank, Saelens, & Kraft, 2004), especially for older people (e.g. (Barnett et al., 2017; Cao, Mokhtarian, & Handy, 2010; Cunningham & Michael, 2004). Several of these studies have examined the built environment-travel relationship through statistical analysis, with the built environment features measured retrospectively through two main approaches: subjective survey measures (e.g. interviews, self-reported questionnaires) and objective data measures (e.g. observational based audit tools and archival based data sets using GIS tools) (Brownson, Hoehner, Day, Forsyth, & Sallis, 2009; Weiss, Maantay, & Fahs, 2010).

Subjective survey measures reveal how participants perceive the quality of their neighbourhood, which may include barriers and opportunities to walking. Perceptions of the environment have been shown to strongly influence older people's walking behaviour (Corseuil Giehl, Hallal, Brownson, & d'Orsi, 2017; Inoue et al., 2011); and health outcomes (Bowling, Barber, Morris, & Ebrahim, 2006). However, face-to-face survey can be expensive to conduct and self-reported instruments have reported limited validity and reliability (Forsén et al., 2010; Weiss et al., 2010), may suffer from recall bias and misrepresent neighbourhood features (Koohsari et al., 2015; Orstad, McDonough, Stapleton, Altincekic, & Troped, 2017), and may result in factitious associations between neighbourhood conditions and health outcomes due to source bias (Mujahid, Diez Roux, Morenoff, & Raghunathan, 2007). On the other hand, objective data measures may involve direct observations to collect primary data of built environment features or using existing data sources of built environment attributes. In direct observation method, observers move through neighbourhoods with a checklist to systematically audit or record neighbourhood characteristics of a street segment or a neighbourhood block (Brownson et al., 2009). Such environmental audit tools have also been developed specifically for older adults such as Senior Walking Environmental Audit Tool (SWEAT) (Cunningham, Michael, Farquhar, & Lapidus, 2005) and Healthy Ageing Research Network Environmental Audit Tool (Center for Disease Control and Prevention's Healthy Aging Research Network, 2009). However, the reliability of built environment attributes on SWEAT could not be assessed thoroughly due to smaller sample size or homogeneous neighbourhoods with limited variability of items (Cunningham et al., 2005).

Other studies have incorporated GIS-based measures to evaluate walkability and physical activities, which are less labour- and time-intensive (D'Orso & Migliore, 2020; Leslie et al., 2007). Leslie et al. (2007) have shown that GIS has the potential to construct measures of the environmental attributes and can be used to develop a walkability index. Using existing data for GIS requires that the data should be managed and cleaned appropriately to suit the research design and a standardised method of cataloguing these measures should be established (Brownson et al., 2009). GIS-based measures may not fully capture the nuanced design features of neighbourhood environment (e.g. street furniture, greenery on streets, inclines, stairs) due to data limitations. Several studies have supplemented objective measures such as audit and/or GIS with subjective measures such as self-reported questionnaire and have shown high degree of disagreement between both the measures (Hajna, Dasgupta, Halparin, & Ross, 2013; Koohsari et al., 2015). More recently, a small number of studies are starting to look at the built environment-travel relationship in real time rather than retrospectively (e.g. (Oliver et al., 2013).

This study aims to add new empirical evidence on the associations between built environment and travel by utilising lifelogging images. Visual lifelogging is a passive photography technique that uses a wearable camera to automatically record individual daily activities from a “first-person” perspective (Kelly et al., 2011). The passively captured images are time-stamped and offer direct measures of travel behaviour, such as travel modes, trip duration and destinations (Kelly et al., 2011), as well as detailed information on various aspects of built environment features that participants encounter while moving around. The details captured by this method could not be easily replicated by other objective methods (Oliver et al., 2013). Using the lifelogging images captured by a wearable camera, the Narrative Clip, we extract information on individual travel behaviour of older adults and various built environment features, identify walking trip patterns taken by participants, and explore how individuals interact with different built environment features in real time during their walking trips.

The paper is based on a study of 30 older adults with different socio-demographic characteristics in three neighbourhoods of Singapore. To our knowledge, this is the first study to apply the visual lifelogging method to explore the real-time built environment correlates of walking patterns in the Singapore context. Located 1° north of the equator, Singapore's climate is characterised by high and uniform temperature, high humidity and abundant rainfall all year round. Since the 1970s, Singapore has been promoting a walkable urban environment to increase liveability as part of an inter-model public transport system (Centre for Liveable Cities, 2016). For example, as part of the walk-friendly environment, covered walkways are provided within 200-400m of mass rapid transit stations and major transport nodes to residences and amenities such as schools and healthcare facilities. Barrier-free accessibility is provided within public housing estates since 2012; over 80% of Singapore's resident population reside in public housing. Safer streets (e.g. silver zones with enhanced road safety features) and resting benches are provided within public housing neighbourhoods to make streets safer for older residents. We hypothesised that these features will facilitate walking and encourage more outdoor activities among older residents. Our findings provide insights on the pedestrian-friendly infrastructure and design features that support active mobility in a high-density urban environment with tropical climate.

By focusing on the older population, this study aims to discover which specific aspects of the built environment are most frequently associated with older adults walking trips and whether there are differences by gender and age groups. Due to reduced physical capacity related with ageing, older people are likely to become more vulnerable to environmental barriers on walking and activity engagement (Barnett et al., 2017). Since older adults are an increasing proportion of Singapore's (and global) population, understanding the built environment correlates of walking for the older population is an imperative of inclusive planning.

The paper is organised as follows. Section 2 briefly reviews the application of visual lifelogging technology in human behaviour and built environment analyses. Section 3 introduces the methods and strategies for data collection, cleaning and analyses. Section 4 presents the main findings from the image data analysis. Section 5 summarises and discusses the planning and design implications of the findings.

2. Literature Review

This section briefly reviews the history of passive photography and its applications in behavioural, health, and built environment studies. We also discuss the limitations and ethical dilemmas of the technique in previous studies and the possibility of its application in analysing the built environment-travel relationships.

2.1 Applications of visual lifelogging

Image-based research has a long history of more than 100 years (Kelly et al., 2013). However, it is with the advancement of digital lifelogging technology that automated, wearable cameras are now capable of capturing thousands of real-time images within a day from the views of individual wearers to reflect their life experiences (Bell, Gemmell, & Gates, 2009; Gurrin, Smeaton, & Doherty, 2014; Kelly et al., 2013; Mann, 1997) Most recently, wearable time-lapse lifelogging cameras as compact and robust image recording devices are becoming ubiquitous due to advances in storage, sensor and technologies (Harvey, Skelton, & Chastin, 2016).

Wearable cameras from brands, such as SenseCam, Vicon Revue, Autographer, Parashoot and Narrative Clip, all include an internal timer to automatically capture images approximately every 20-30 seconds within a 24-hour period (Hodges et al., 2006). The "disengaging design" of these cameras means that they do not require user action nor do they interfere much with users' daily lives (Ljungblad, 2009). As the digital lifelogging technology matures, the focus of passive photography as well as other lifelogging research in recent times has shifted towards eliciting meanings from lifelogs and enquiring how this information may influence individual's wellbeing, lifestyle or behavioural patterns (Doherty et al., 2011; Kahlert, 2016).

As opposed to self-report assessment methods such as travel or health surveys, data collection through lifelogging technologies does not require any additional actions from the respondents, thus avoiding misinterpretation of questions in survey and reducing reliance on respondent recall that could be biased due to social desirability and fallibility of human memory (Harvey et al., 2016; Kahlert, 2016; Kelly et al., 2013). In other words, personal data collected through lifelogging devices are more likely to objectively reflect what actually happened instead of what the participants wished they had done (Kelly et al., 2013). Recording from a "first-person point-of-view", this data collection method enables researchers to explore aspects of participants' lives that might not be accessible in alternative objective methods (e.g. direct observation) (Kelly et al., 2013).

Wearable lifelogging cameras have been applied to investigate and measure human behaviour, such as sedentary and active lifestyles, social participation, and travel behaviour of individual participants (Kelly et al., 2011; Kelly et al., 2012; Kerr et al., 2013; O'Loughlin et al., 2013) (see Table 1). Images captured through lifelogging cameras may convey multiple layers of the environment context of behaviour and capture details from everyday activities such as environmental features and persons interacted with and interlinks between behaviour (Doherty et al., 2011; Harvey et al., 2016). Compared with other lifelogging tools, visual lifelogging provides the "closest alternative to direct observation" of human behaviour with the need for inferring from the devices (Kelly et al., 2011). This is especially useful when analysing individual travel behaviour or physical activity engagement. For example, while individual travel mode and destination choices can be inferred from other tools such as accelerometers and global positioning systems (GPS) devices, this information is easily observable from passively captured photos (Kelly et al., 2011). Moreover, the time-stamps on the images convey information of when an individual activity (event) happened and make it possible to accurately estimate how long the event lasted (Harvey et al., 2016). Wearable cameras are a potentially new tool that can replace or complement traditional self-reported travel surveys.

Table 1 Examples of passive photography applications in various fields

Application	**Example case studies**
Travel behaviour	Kelly et al. (2011) examined the active and sedentary travel behaviour of people. Doherty, Kelly, & Foster (2013) identified the transportation choices among adults and adolescents.
Assessing the built-environment	Kerr et al. (2013) identified activity behavioural patterns of adult cyclists using wearable cameras and accelerometers. Kelly et al. (2012) compared the difference in the duration of journey-to-school trips for children (aged 13–15) between self-report and that observed from time-stamped lifelogging images.
Evaluating health and lifestyle behaviour	Lam et al. (2013) examined the time spent outdoors in natural environments using GPS and wearable cameras among different age groups. Harvey et al. (2016) assessed older adults' experiences of wearing lifelogging cameras and collected information on the context of their sedentary behaviour, which would provide insights on targeted interventions for reducing sitting time. Doherty et al. (2011) incorporated visual lifelogging across 3.5 years to identify a range of lifestyle traits. Silva et al. (2013) examined the role of wearable cameras in memory aid and found the camera performed positively in enhancing cognition for healthy adults.

Absence of initiation from the wearer to operate the camera has made the lifelogging device acceptable and easy to use for older people (Harvey et al., 2016). Previous studies have explored the feasibility of using wearable cameras among older participants. Sheats et al. (2013) recruited older adults along with adolescents to measure the positive or negative influences of different built environment features on physical activity. Harvey et al. (2016) used wearable cameras along with objective activity monitors to determine the context of sedentary behaviour in older adults. Wilson (2004) explored the usability and acceptance of wearable cameras in understanding the day-to-day functioning of older adults suffering from chronic pain. Most of the participants from these studies found the camera to be acceptable to wear, not intrusive or an interference with their daily activities. This allows researchers to objectively examine participants' daily experiences and behaviour (Harvey et al., 2016; Sheats et al., 2013; Gemma Wilson, 2014).

2.2 Limitations and ethical dilemmas

There are several technical and data management challenges of using wearable cameras for image-based research. First, poor quality or invalid images may be produced due to poor operation of the camera, such as pressing the wrong button to turn on/off the camera, incorrect positioning of the camera (A. R. Doherty, S. E. Hodges, et al., 2013; Kerr et al., 2013; Silva, Pinho, Macedo, & Moulin, 2016), or low lighting condition (A. R. Doherty, S. E. Hodges, et al., 2013; O'Loughlin et al., 2013). Malfunctioning of these devices may also lead to uncaptured images (A. R. Doherty, P. Kelly, & C. Foster, 2013; Sheats et al., 2013). To mitigate these operational challenges, researchers may choose a wearable camera that does not have any buttons or only a few buttons and guide participants to wear the camera appropriately (i.e. at about chest level) (A. R. Doherty, S. E. Hodges, et al., 2013; A. R. Doherty, P. Kelly, et al., 2013).

Second, the analysis of passively captured photos can be time-consuming as the volume of data generated is large—about 2000-3000 photographs per 12 hours of wear (A. Doherty, P. Kelly, & C. Foster, 2013; A. R. Doherty, P. Kelly, et al., 2013; Kelly et al., 2013). Manual coding of these photographs could be labour intensive and can sometimes lead to errors (Kerr et al., 2013). Automated techniques including data management platforms and machine learning algorithms to process the lifelogging images are in their early stage of development and the accuracy of the output is questionable. Additionally, passive photography may not be suitable for large-scale studies due to difficulties in data processing and coding (Kelly et al., 2012).

In addition to the data analysis challenges , the collection process of lifelogging image data may have ethical dilemmas. A key challenge is the intrusion of wearers' privacy, especially in sensitive situations, e.g. washrooms (A. R. Doherty, S. E. Hodges, et al., 2013; Oliver et al., 2013). The privacy of third parties (e.g. family members, work colleagues, strangers) may also be jeopardised as autonomous cameras may capture them without their consent (Doherty et al., 2013). To mitigate these issues, previous observational studies have developed ethical codes to formalise the technique of using wearable cameras (e.g. Kelly et al., 2013). These include advising participants to remove the camera whenever they wish, especially in places where photography is prohibited (e.g. banks, schools, public toilets) or if they feel threatened (e.g. crime scenes) (Harvey et al., 2016), and allowing participants to review and delete unwanted images (Oliver et al., 2013). To protect the privacy of third parties, Kelly et al. (2013) have suggested seeking verbal approval prior to wearing the camera even in situations where written consent from these parties may not be essential. Furthermore, the research team should restrict direct access to lifelogging images to the team to protect confidentiality of the participants' data (Harvey et al., 2016).

In sum, visual lifelogging allows researchers to access people's behaviour and environment in real-time from the perspective of the participants. This provides an opportunity for transportation researchers to gain new insights on the built environment-travel links that might not have been revealed in previous studies using other methods. However, the challenges in data collection and processing and the related ethical dilemmas may limit the application of this method. This study adds to the application of passive photography in travel behaviour analysis and environmental audits through a pilot study focusing on older adults. By properly training the participants and interviewers and developing a coding framework and platform, we aim to control the quality of passively captured photos and facilitate the processing and analysis of lifelogging image data.

2.3 Relationship between travel and built environment

The relationship between travel behaviour and built environment has long been studied in the field of transportation. Researchers found that certain built environment characteristics, e.g. mixed land use, proximity to facilities and street connectivity, could facilitate active travel among individuals (Brownson et al., 2009; Christiansen et al., 2016; Hong & Chen, 2014). This is especially true among older adults, who are more likely to experience functional and health declines and are therefore, more sensitive to outdoor environment (Cerin et al., 2013; Chaudhury, Campo, Michael, & Mahmood, 2016; Gómez et al., 2010). In Singapore, easy access to destinations (e.g. parks, open spaces), neighbourhood safety and provision of covered walkways are found to promote walking among older residents (Song, Yap, Hou, & Yuen, 2020). Another study in Singapore also indicates that perceived access to recreational facilities has positive effects on older adults' daily walking trip frequency (Hou, Yap, Chua, Song, & Yuen, 2020). Our research will add real-time data analysis, aiming to explore older adults' walking travel patterns and their associations with neighbourhood built environment features in real time with the technology of passive photo.

3. Methodology

The visual lifelogging was conducted as part of a larger research project, XXX [Blinded for peer review]. The aim of this study is to explore which dimensions of built environment features (e.g. walkways, street signs, street furniture, open/green spaces) are highly associated with older adults' daily walking trips, and which types of places (e.g. public transit hubs, community centres, markets) are likely to be frequently visited in their everyday life space. We expect that older adults of different age and gender subgroups would vary in their usage of different built environment features during walking and the choices of walking trip destinations.

3.1 Data collection

The collection of valid and reliable lifelogging image data involved several steps, including the recruitment and training of participants and the collection of the images.

3.1.1 Participant recruitment and trainings of interviewers and interviewees

Equipment: This research used the Narrative Clip 2 wearable lifelogging camera. The camera has a storage capacity of 4000 photos and captures 8 megapixel photos at an interval of 30 seconds. The camera does not have any buttons and automatically turns off when faced down, thus mitigating the operational challenges of utilising the lifelogging device (Doherty et al., 2013). The captured photos are downloadable to a local storage-MacBook with the help of the Narrative Application.

Interviewer Training: We mobilised 10 student assistants and 5 researchers to help with data collection. The tasks involved visiting the participant at the end of each day for one week to download the photos to a MacBook provided by the research team, reviewing the photos with the participant, asking participant's travel information each day on a (simplified) travel diary and assisting the participant to charge and get their camera ready for the next day. To mitigate the intrusion of wearers' privacy, we asked student assistants to delete unwanted photos during the photo reviewing process when requested by the participants (Oliver et al., 2013). Student assistants also sent a reminder to the participants every morning to wear the camera before they step out of their residence.

Participant Recruitment and Training: Participant eligibility criteria included age (55 years and above), Singapore citizens or permanent residents, residing in three study neighbourhoods. These neighbourhoods were built over different periods and have a higher proportion of older residents. As part of Singapore's public housing townscape, the three neighbourhoods have good access to public transport and active mobility infrastructure. For example, the average distances between residence and the nearest MRT (Mass Rapid Transit) stations and bus stops in the three study neighbourhoods are 361 and 123 meters, respectively, while the average distance between residence and the nearest cycling infrastructure is 418 meters.[1] Thus, residents in the 3 neighbourhoods have other transport mode choices besides walking.

[1] The details of descriptive statistics of access to public transport and other infrastructure can be found at Hou et al.'s (2020) study, which was conducted in the same 3 neighbourhoods funded by the same research project.

We publicised the project at community outreach events, through the display of posters, circulation of flyers and email fan-outs (Sheats et al., 2013). We then called each potential participant who indicated interest. The participants who agreed to join the study were provided with details of the study and their informed consent was sought. We recruited eligible participants who were willing to wear the camera for 1 week.

Based on pilot testing, we drafted an instruction manual to inform the participants how to wear the camera properly (see Appendix I). As the camera captures photos passively, there is little action required from the participants to operate the camera. Hence, the instruction manual and participant training were designed to mitigate ethical dilemmas related with the wearable camera (Oliver et al., 2013). For example, to protect the privacy of wearers and third parties, we asked participants to wear the camera only when they step out of their residences and take off or turn off the camera in places that require privacy or security (e.g. washroom, swimming pool, bank) or whenever they feel threatened (Oliver et al., 2013). We also gave suggestions on how to respond to third parties when the wearers were questioned by them.

To reduce any influence the camera might have on participants' behaviour, participants were reminded not to alter their daily travel behaviour, routines or routes for the research study. We assured participants that they are not required to travel outdoors every day during the time of their participation in the research. That is, if their usual routine involved staying at home some days of the week, then they could continue the routine and stay at home during the data collection period. We emphasised that participants should not alter their routes, mode of transport or trips in response to the research study and that they should follow their normal weekly routines. Participants could use any transportation method and travel to any destination within Singapore while wearing the camera.

Research on lifelogging has shown that the number of participants involved in previous studies varies from 1 to 40 participants, based on the duration and type of research (Doherty et al., 2011; Lam et al., 2013; Silva et al., 2016; Thoring, Mueller, & Badke-Schaub, 2015). In our study, we recruited a total of 30 participants, 10 participants per study neighbourhood. Table 2 shows the socio-demographic profiles of the participants.

Table 2 Socio-demographic profiles of participants (n=30)

Variables		**Number**	**Percent**
Gender	Male	9	30%
	Female	21	70%
Age Group	55 - 64	5	16.7%
	=/>65	25	83.3%
Ethnicity	Chinese	24	80%
	Malay	2	6.7%
	Indian	3	10%
	Others	1	3.3%

3.1.2 Collection of lifelogging images

Research on lifelogging indicates that data collection can vary from a few hours to several days, depending on the kind of information the research team is seeking to extract. Human behaviour studies such as on health status and travel patterns tend to study participants for three to seven days to garner a stable estimate of habitual behaviour and a sufficient number of case examples (Kelly et al., 2012; Kerr et al., 2013). Thus, our study asked each participant to wear the lifelogging camera for 7 days.

The main data outputs from wearable cameras are jpeg-format images, which are passively captured at 30 seconds time intervals. In total, we collected 82,287 images across 210 days. Participants were given the freedom to review and delete the photos they did not wish to be included for data processing. At the time of reviewing lifelogging images, our interviewers also asked participants to complete a simple travel diary that collected information on where, how and when they travelled and if they met people while travelling. The travel diaries were used to validate the trips identified from passive photography. We also conducted a short survey at the beginning of the photo activity that recorded participants' socio-demographic information.

3.2 Data processing

Wearable cameras produce a large volume of data. Many previous studies have reviewed individual images manually to identify participants' journeys or the built environment features that may enable or hinder physical activity (e.g. (Kelly et al., 2011; Sheats et al., 2013). Processing the data may involve manual or automatic reviewing of images. Recent advancement in automatic reviewing using machine vision such as deep learning and convolutional neural networks (CNN) have allowed the processing of large data sets to identify various features in images (Nweke, Teh, Al-Garadi, & Alo, 2018). However, processing of large dataset of egocentric/first-person images are still at their early stage of development (Segawa, Kawamoto, & Okamoto, 2018). Castro et al. (2015) showed the prediction of daily activities from egocentric images using CNN. They successfully identified 19 daily activity classes (Castro et al., 2015). However, the model misclassified certain activities due to visually similar nature of such activities; and the model failed to generalise activities across different users, which meant that the model had to be fine-tuned for every new user (Castro et al., 2015). While certain built environment features can be easily identified through trained neural networks, first-person activity recognition is more complex, especially to contextualise the role of built environment features in determining the person's activity. Crucially, neural networks need to be trained for specific feature classes across multiple users (Castro et al., 2015). Currently, such a rich dataset for egocentric images is lacking (Bolanos, Dimiccoli, & Radeva, 2016), especially in the context of Singapore. We tested the accuracy of using a machine learning algorithm for simple tasks for this study and found the performance of CNN subpar when compared to manual coding.[2] Based on these constraints and

[2] Based on our coding framework indicated in Table 1, we investigated using the CNN approach to detect scenes (e.g. activities, type of places, infrastructure) from the lifelogging images taken by the participants in a randomly selected 3-4 days of the 7-days' photo-capturing activities. The results indicated:
* Codes that can be trained using existing trained network: Person, Bicycle, Bus (exterior image), Train (exterior image), eating, bus stop, covered walkway, pedestrian crossing, cycling path, streetlights, traffic lights, street signs, street furniture, stairs, ramps, trees, cycling (if the cycle handle is visible), driving (if the steering wheel is visible)
**Codes that cannot to be trained using existing trained network: bus (interior), train (interior), chatting, standing, sitting, shopping, exercise, home, playground, park, void deck, public open space, market, supermarket, food court, shop, mall, hospital, clinic, community centre, senior activity centre, transaction service and indoor fitness.

challenges, we chose to manually code and label the passively captured egocentric images to extract relevant information for this study.

3.2.1 The coding framework for labelling lifelogging images

To ensure robustness and consistency of image analysis, a coding framework was developed with six main classes of information (see Table 3): 1) persons (who interacted with the participants); 2) mode of transport used by the participants; 3) activities undertaken by the participants; 4) transport and pedestrian infrastructure encountered; 5) type of places visited; and 6) natural features encountered. Some features identified from the images can be found in Figure 1.

Table 3 The coding framework for identifying various features captured in the images

Category	General	Mode of Transport	Activities	Transport and Pedestrian Infrastructure	Type of place	Natural feature
Features identified	–person	–walking –cycling –bus –train (i.e. Mass /Light Rapid Transit, MRT/LRT) –driving –car passenger	–sitting –standing –chatting –eating –shopping –running –exercise	–MRT station –bus stop –covered walkway[3] –pedestrian crossing –cycling path –street lights –traffic lights –street signs –street furniture –stairs –ramps	–home –playground –park –void deck[4] –public open space[5] –supermarket –(wet/dry) market –food court –shop –mall –hospital –clinic –community centre	–trees

[3] The urban design requirements of covered walkways can be accessed https://www.ura.gov.sg/Corporate/Guidelines/Development-Control/Non-Residential/Commercial/Covered-Walkways

[4] Void decks are spaces located on the ground floor of public housing apartment blocks developed by Singapore's Housing and Development Board (HDB) that are left open to provide a place for residents to meet and socialize. See https://www.nhb.gov.sg/~/media/nhb/files/resources/publications/ebooks/nhb_ebook_void_decks.pdf

[5] Since parks and playgrounds are singled out as separate categories, here public open spaces refer to other outdoor spaces that are open for public access and public recreation.

					–senior activity centre –religious establishments –transaction services (banks, post offices) –indoor fitness facilities (e.g. gyms, swimming pools)	

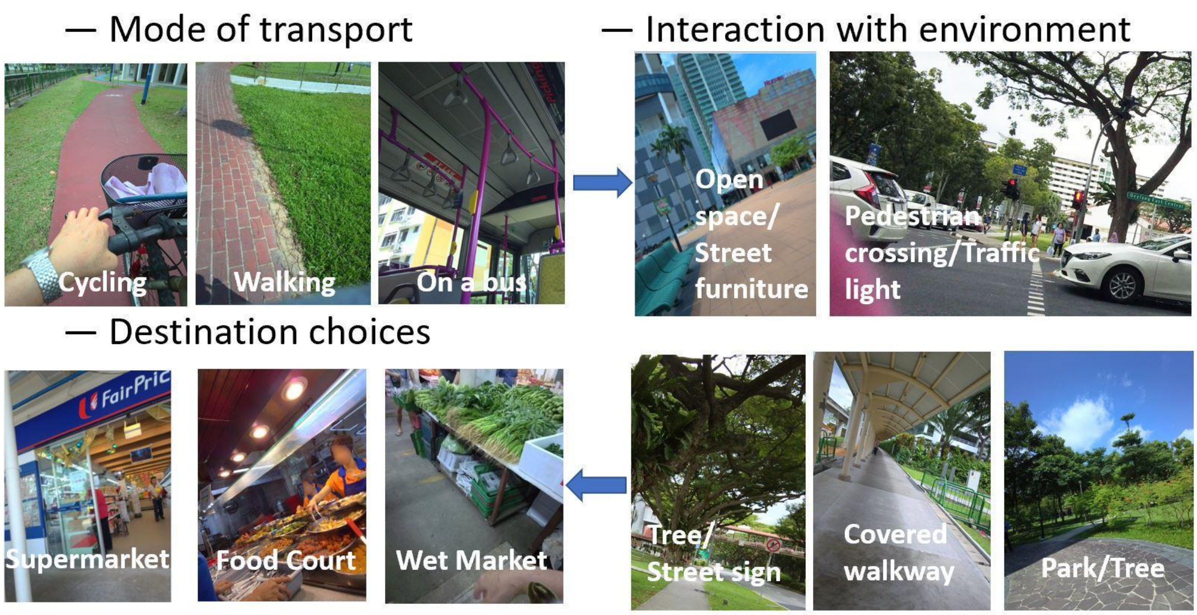

Figure 1 An example of environment and individual behavioural features detected from the passively captured photos

In the absence of available labelling software, a software was developed by the research team to provide a platform to review and manually tag or label the images with reference to the coding framework. We trained 24 student assistants to review and label the lifelogging images that cover all 7 days the 30 participants wore the camera (210 days in total). Specifically, the presence or absence of features listed in the coding framework was coded as 1 and 0, respectively. Poorly captured images with no identifiable information such as those covered intentionally or unintentionally by participants, were marked as “not useful” and excluded from further data analysis. The number of useful images is

55,057, constituting 66.9% of total images received for review. In total, 201 days of outdoor activities taken by the 30 participants were identified from the useful images.

3.2.2 Identifying walking trips

The outputs of manual image labelling from the software were CSV tables that contain information on the unique IDs of each image, the date and time stamp of each image, and the coded information on the environmental and behavioural features identifiable from each image (see Figure a3 in Appendix II for an example of the output table). We added the unique IDs (anonymised and without personal identifiers) of each participant into the tables to facilitate further analysis.

We checked the consistency of each participant's daily activities by looking through the type of travel or activities (e.g. shopping, walking) that were co-labelled in the same image and corrected those that conflicted with each other. In total, 2038 records were checked and corrected due to errors in the labelling of activities.

To identify travel by different modes for each participant-day, we processed the CSV output table in the following steps:[6]

- Sort all the useful images by their time stamps;
- Calculate the time intervals between neighbouring images;
- Group the images based on the coding for a mode of transport (e.g. walking, bus, MRT/LRT train) and time interval; if the time interval between an image and the previous useful one is less than 15 minutes and both images have coding for a mode of transport equals to 1, the two images are considered as one trip (event) and marked with the same ID; otherwise, they were assigned with different event IDs.[7]

[6] Similar processes have also been applied to identify the activities (e.g. sitting, eating, shopping, chatting) and their associated characteristics taken by each participant in a day.
[7] We also experimented with other cut-offs of time intervals (e.g. 5 minutes, 10 minutes), but the results do not differ significantly.

We then chose from all trips (events) where walking is identified as the mode of transport and summarised the tables to get the following information of the identified walking trips. First, the duration of each walking trip (referred as travel event) was calculated as the difference in the time stamped between the first and the last image of a trip. Those walking trips with only one image identified (duration less than 1 minute) is dropped from further analysis. Second, the type of origin and destination locations of walking trips were identified based on the value of the "type of places" for the first and last image of the same event, respectively; if a place type was coded as 1 in the first/last image, it was assigned as the origin/destination location type of the travel event.[8] Finally, the built environment and other features encountered during each travel event were identified by using the maximum value of each feature for all images belonging to the same walking trip event. The output table, thus, not only includes information on the origin, destination, and duration of all trips taken by walking, but also the built and natural environment features individual participants encountered and experienced during the walking trips. This provides insightful information for urban planning and design interventions.

We also cross-checked with participants' travel diary report by comparing the daily walking trip frequency from the two methods. On average, the number of walking trips per day identified based on image analysis is larger than the daily walking trip frequency extracted from self-reported travel diaries by 0.63 per person-day. This could be attributed to recall effect, e.g. participants may not have reported some trips in the diary. Moreover, we observe that walking trips taken by the older participants can be discretionary in nature, such that they may stop at a public space to talk to some acquaintance or sit at the bench for a rest before reaching a final destination of the trip (e.g. shops, transit stops, markets). If the stopping time in a walking trip is more than 15 minutes, the trip is split into two or more trips based on our data processing rule. This may be another reason for the difference in the daily walking trip frequency calculated from the two data collection methods.

[8] Similar processes have also been applied to identify the duration and origins/destination of other trip events (e.g. bus, train, cycling) taken by each participant in a day.

3.3 Data analysis

From the coded travel diary, we summarised the characteristics of the participants' daily walking travel in several aspects: 1) number of trips taken per day (daily trip frequency) by walking; 2) average duration of walking trips taken per day (in minutes); 3) interactions with environment features during walking; 4) distribution of destination choices.

We also compared how the four aspects of travel characteristics differ among older participants of different age/gender groups. To conduct this analysis, we linked the output table with the data from the survey questionnaire that includes participants' socio-demographic characteristics. We applied Fisher's exact test (Fisher, 1970) to explore whether there is any statistically significant relationship between age/gender categories and each type of built environment features encountered during walk or the type of place where people choose to walk to.

We also differentiated daily walking trips by three duration intervals of less than or equal to 10 minutes (short-duration), 10-20 minutes (medium-duration), and more than 20 minutes (long-duration). Although walking trips less than 10 minutes are usually ignored in physical activity studies because they are less important in terms of health benefits[9], we still retain those short-duration walking trips in this analysis as these trips might be important for older adults to access local destinations to fulfil their daily needs such as shopping, eating and socialization. Another time threshold of walking trips is set as 20 minutes, which follows Singapore's long term goal of building "20-minute towns" that all residents can access their nearest neighbourhood centre within 20 minutes by active transport modes.[10] Walking trips longer than 20 minutes are expected to be less often made by older people. We explore how older adults' older adults' walking characteristics vary with the

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[9] According to the "Guidelines for data processing and analysis of the International Physical Activity Questionnaire (IPAQ) — Short and Long Forms" (Page 10; https://docs.google.com/viewer?a=v&pid=sites&srcid=ZGVmYXVsdGRvbWFpbnx0aGVpcGFxfGd4OjE0NDgxMDk3NDU1YWRlZTM),
"(t)he rationale being that the scientific evidence indicates that episodes or bouts of at least 10 minutes are required to achieve health benefits."

[10] The Land Transport Master Plan (LTMP) 2040 developed by the Land Transport Authority of Singapore promotes "20-minutes Towns and a 45-minutes City" to encourage health and safe travel for all. See https://www.lta.gov.sg/content/ltagov/en/who_we_are/our_work/land_transport_master_plan_2040.html

length of trips by comparing the number of walking trip-making per day and the destination choices of walking trips by the three time intervals. Detailed discussions of the data analyses results are presented in the next section.

4. Results

4.1 Daily walking trip frequency

Table 4 reports the descriptive statistics of the number of walking trips per day among the older participants of different age and gender subgroups. The average number of walking trips per day is 4.17. There is no significant difference in the number of daily walking trip-making across gender. These findings match observations from a survey with 1002 older adults in Singapore that older adults on average undertake around 4 trips by walking per day with no significant gender differences detected (Hou et al., 2020).

Table 4 Descriptive statistics of the number of walking trips per day and results of two-sample t tests

	Total number of participants	Total number of days	Mean	Std. Dev.	Min	Max	Two-sample t tests: T-value (degree of freedom)
All participants	30	175	4.17	2.49	1	13	
By gender							
Male	9	53	3.98	2.36	1	10	male vs. female: t(728)= -0.014
Female	21	122	4.25	2.55	1	13	
By age groups							
55-64	5	31	4.32	2.10	1	10	55-64 vs. 65-74: t(123) = -0.076 65-74 vs. 75+: t(142) =1.43 55-64 vs. 75+: t(79) = 1.13
65-74	16	94	4.36	2.61	1	13	
75+	9	50	3.72	2.46	1	12	

Following the national statistical definitions by Singapore Department of Statistics (2016) and previous findings by Kang, Tan, and Yap (2013) and Yuen, Withanage, and Nair (2019), the age variable is subdivided into three age bands, namely, the "emerging-old" for persons aged 55-64 years, "young-old" for persons aged 65-74 years, "old-old" for those aged 75 years and over.[11] The differences in daily walking trip frequency are not significant across age groups. In other words, the propensity to undertake around 4 trips by walking per day among those participants is not diminished as people aged.

4.2 Duration of walking trips

As discussed in Section 3.3, trip duration here refers to the number of minutes observed for each trip identified in the travel diary generated from the coded information of lifelogging images. Descriptive statistics are generated for those participant-days that are observed to have at least one walking trip. Table 5 indicates that the average walking trip duration of the participants is 14.5 minutes and does not differ significantly between male and female older adults. However, those aged 75 years and older have the shortest average walking trip duration per trip of 11.4 minutes, which is significantly shorter as compared with those aged 55-64. This implies that the age of 75 may be a threshold at which physical constraints associated with aging became evident so that older people choose to walk shorter distance in their daily lives (Giuliano, Hu, & Lee, 2003).

Table 5 Descriptive statistics of duration per walking trip (in minutes) and results of two-sample t tests

	Total number of participants	Number of observations	Mean	Std. Dev.	Min	Max	Two-sample t tests: T-value (degree of freedom)
All participants	30	730	14.47	31.09	1.07	527.02	
By gender							
Male	9	211	14.45	37.30	1.07	500.43	male vs. female: t(728)= -0.014
Female	21	519	14.48	28.23	1.07	527.02	
By age groups							
55-64	5	134	15.14	24.23	1.07	210.50	55-64 vs. 65-74: t(542) = -0.14
65-74	16	410	15.64	38.23	1.07	527.02	65-74 vs. 75+: t(594) = ***1.48***
75+	6	186	11.41	11.96	1.07	79.80	

[11] We have not singled out those aged 85 years and over as a separate group because there are only two people of this age band in the sample, with only 41 walking trips identified in the 14 days that the participants wore the lifelogging camera. This number is too small to draw any valid conclusion on the walking behaviour of this age group in general.

	55-64 vs. 75+: t(318)=1.81*

Note: ***Italic and bold***, p<0.1; *, p<0.05; **, p<0.01; ***, p<0.001

We also counted the number of walking trips undertaken per day by the three time intervals of walking duration (i.e. <=10 minutes, 10-20 minutes, >20 minutes). Table 6 shows that more than 58% (i.e. 426 out of 730) of the walking trips identified from the passively captured images of the 30 older participants are less than 10 minutes and around 25% of the walking trips are in 10-20 minutes. Viewed on a daily basis, among the average number of 4.2 walking trips undertaken by older adults per day, around 2 trips are within 10 minutes, 1 trip is between 10-20 minutes and another 1 trip is more than 20 minutes. The differences in the average daily trip frequency of short-duration (<=10 minutes), medium-duration (10-20 minutes) and long-duration walks are significant (results not shown). Moreover, the propensity of undertaking more short-duration daily walking trips instead of longer ones is consistent across all gender and age groups. This lends support to the importance of providing daily destinations such as shops, eateries, and community clubs within short walk distance to residences or transit hubs to improve older residents' access and their use of those facilities.

Table 6 Number of walking trips per day by time intervals of duration per trip

	Walking trips <= 10 minutes			Walking trips 10-20 minutes			Walking trips >20 minutes		
	Total number of trips	Number of days observed	mean (std. dev.)	Total number of trips	Number of days observed	mean (std. dev.)	Total number of trips	Number of days observed	mean (std. dev.)
All participants	426	175	2.43 (2.06)	183	175	1.05 (1.17)	121	175	0.69 (0.81)
By gender									
male	133	53	2.51 (2.07)	50	53	0.94 (1.03)	28	53	0.53 (0.67)
female	293	122	2.40 (2.06)	133	122	1.09 (1.23)	93	122	0.76 (0.85)
By age groups									
55-64	78	31	2.52 (1.71)	34	31	1.10 (1.16)	22	31	0.71 (0.74)
65-74	235	94	2.50 (2.26)	104	94	1.11 (1.13)	71	94	0.76 (0.80)
75+	113	50	2.26 (1.87)	45	50	0.90 (1.27)	28	50	0.56 (0.86)

4.3 Interactions with built environment during walking trips

The utilisation and interaction of older adults with the built environment and their environment-walking-travel relationship differs by gender and age subgroups. We examined the percentage distribution of walking/cycling infrastructure and other built environment features (e.g. street furniture, street lights, pedestrian crossings, covered walkways) during walking trips by calculating the ratio of the number of walking trips where an environment feature appeared to the total number of walking trips. The Fisher's exact test is applied to explore the appearance of each type of built environment feature in the walking trip and older participants' gender and age.

1) Overall distribution

Figure 2 shows that the participants frequently walk through public open spaces, places with trees, void decks and covered walkways. This is in line with our expectation that these age-friendly built environment features could facilitate walking among older residents. A key element appears to be the presence of shade and shelter. The void deck is part of the public housing block design typology where the ground floor of HDB housing blocks is left void of dwelling units by design to provide residents with proximate spaces for social and community uses like senior activity centre, residents' corner, wedding and funeral events (National Heritage Board, 2013). It also functions as a sheltered thoroughfare that pedestrians can pass through in their neighbourhoods without being exposed to sun or heavy rain (P. Koh, B. Leow, & Y. Wong, 2015). In the case of Singapore where the temperature do not fall below 23-25ºC even during the night and heavy rainfalls occur 167 days per year on average (Meteorological Service Singapore, 2020), the provision of shelters for pedestrians are likely to improve the comfortableness of walking trips. Moreover, walking through the void decks may also increase their chances of encountering friends and acquaintances for casual chit-chat and other interaction opportunities.

Places with trees provide shade for pedestrians, which are likely to make walking more comfortable and pleasant. In a similar way, covered walkways provide shade and protection from local weather challenges. These facilities are usually placed within 200-400 metres of MRT stations/major transport nodes or high footfalls (e.g. Central Areas, Regional Centres and Key Growth Areas) or as the link between two public areas (Urban Redevelopment Authority, 2020), which could be another important reason for them to be frequently utilised by pedestrians. This is consistent with previous findings that covered walkways play positive roles in older adults' walking travel and physical activity for transport purposes (Hou et al., 2020; Song et al., 2020).

Moderately encountered built environment features during walking trips include stairs and places with street lights, street furniture, pedestrian crossings, and street signs. Playgrounds, parks, places with traffic lights and the ramps are occasionally used by older adults during their walk. The differences in the occurrence of pedestrian crossing and traffic lights in walking trips possibly reflect participants' route selection (they select crossing places with traffic lights) or the presence of pedestrian crossing without traffic lights in the three study neighbourhoods, which could be a negative factor influencing older adults' propensity to undertake more walking trips per day according to the results of a previous study (Hou et al., 2020) and pose potential hazards for older pedestrians (Yun, 2019). Cycling paths are rarely used by older adults, suggesting that older people may select to avoid and interpret these paths as dangerous and hazardous, given the purposive intent of the path for cyclists, not pedestrians.

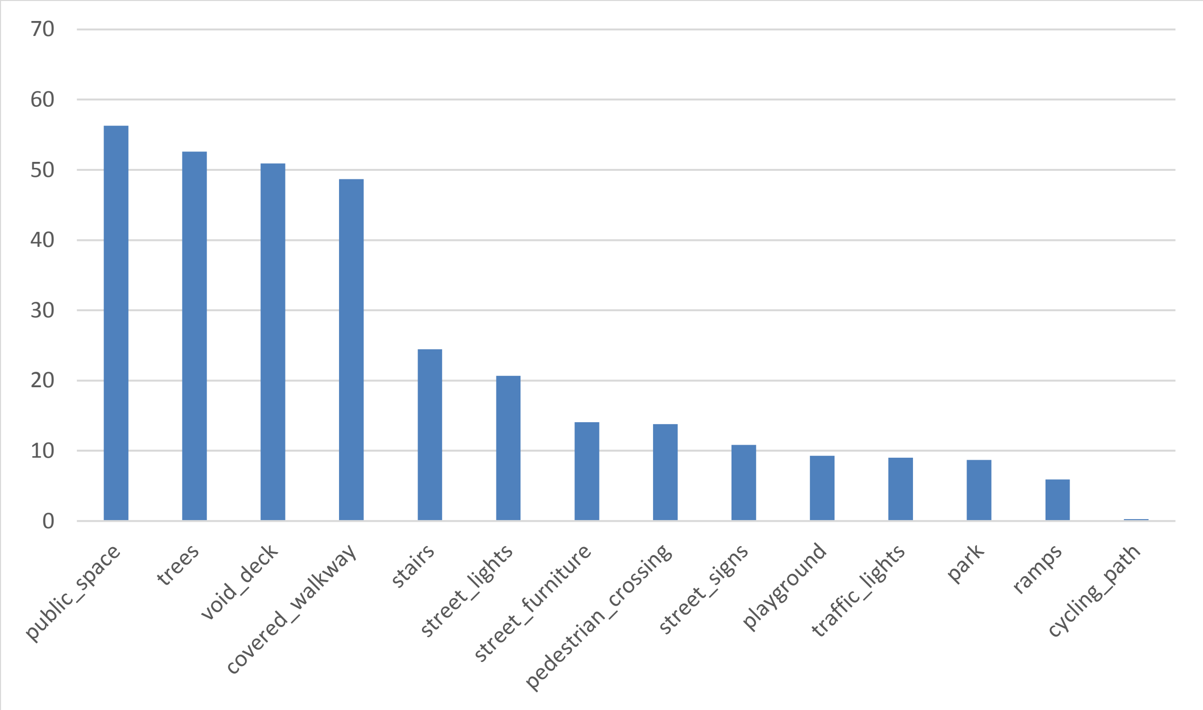

Figure 2 Percentage distribution of built environment features encountered during walking trips

2) By Gender

Public open spaces, places with trees, void decks and covered walkways are most frequently visited by both older men and women (see Figure 3). Fisher's exact test indicates there is a statistically significant relationship between gender and the occurrence of playgrounds during walking trips (p=0). Compared to older males, older females more frequently walk through playgrounds, which could also serve as meeting points for informal social interactions with friends, neighbours and other people. The difference by gender in the usage of other built environment features during walking is not statistically significant (see Table a3 in Appendix II).

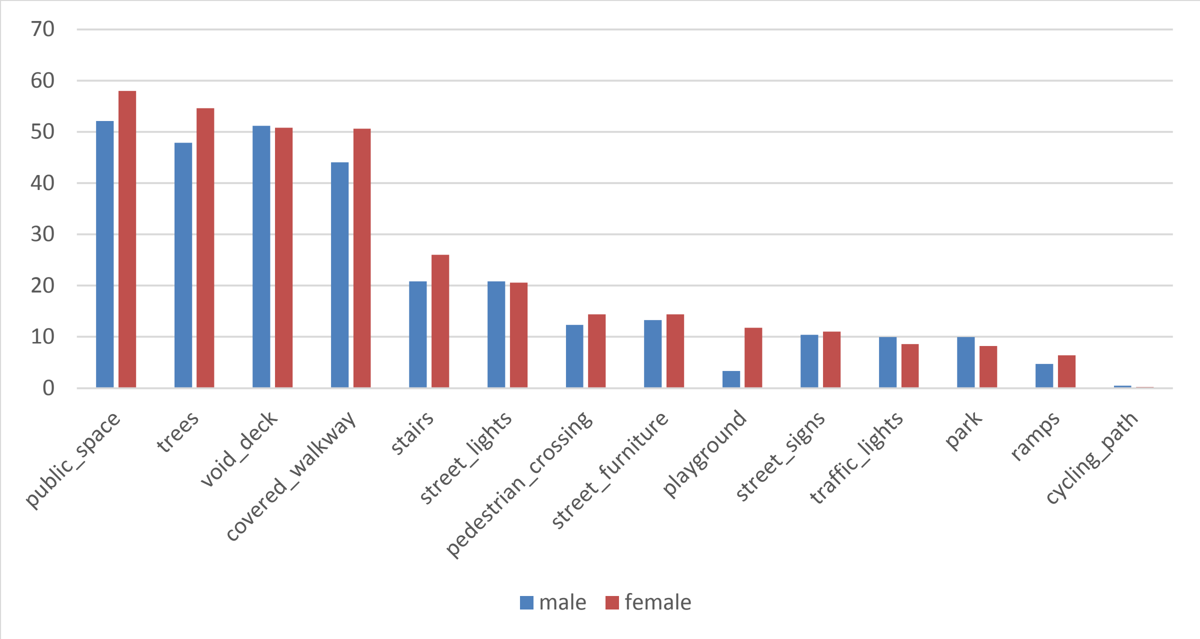

Figure 3 Percentage distribution of built environment features encountered during walking trips by gender

3) By Age Groups

Figure 4 indicates that commonly used built environment features among the three age bands include public open spaces, void decks covered walkways and spaces with trees, while the least frequently used features include cycling paths and ramps. The frequently used features are anticipated as these spaces are conducive to social interactions.

The results of Fisher's exact tests suggest that there is a significant relationship between age bands and the usage of covered walkways (p=0.012), void decks (p=0.022), spaces with trees (p=0), and street furniture (p=0.002) (see Table a3 in Appendix II). The young-old participants are the most frequent users of walkways with tree shelters, followed by the old-old residents. Compared with the emerging-old, the young-old and old-old also more commonly walk along void decks and pathways with shelter. This result possibly reflects that those aged 65 and over have relatively higher requirements for the comfortableness of pathways such as those with covers or tree shades that would protect them from the weather. As many may have stepped into retirement age, they might have a relatively flexible time schedule that allows them to make choices on the routes of walking trips. In contrast, those aged 55-64 belong to the "sandwiched generation" (Kang et al., 2013) who are in the working age and have a tighter schedule, which might not allow them to pay as much attention to the comfortableness of walking trips as their senior cohorts.

Another trend is that the old-old residents most commonly use space with street furniture, followed closely by the young-old. This complements the previous finding that the perceived availability of street furniture such as sitting facilities) is associated with more weekly minutes of walking for those aged 65 years and older (Cerin et al., 2014). One possible explanation is that as people aged, their physical constraints also increase such that the provision of street furniture (e.g. benches) would allow them to take a rest during walking trips.

Moreover, the relationship between age bands and the utilisation of parks during walking is weakly significant at $p<0.05$ level (Fisher's exact test: $p=0.065$). The emerging-old and young-old exhibit relatively low frequency in the use of parks when walking around the neighbourhood, while the old-old walk through parks slightly more frequently. But as compared with other public areas such as open spaces and void decks, parks are in general less frequently utilised by older pedestrians. Although unclear, it is speculated that parks in the three study neighbourhoods may potentially be poorly maintained and/or not within close proximity to their homes and further research is required before a conclusive statement could be made.

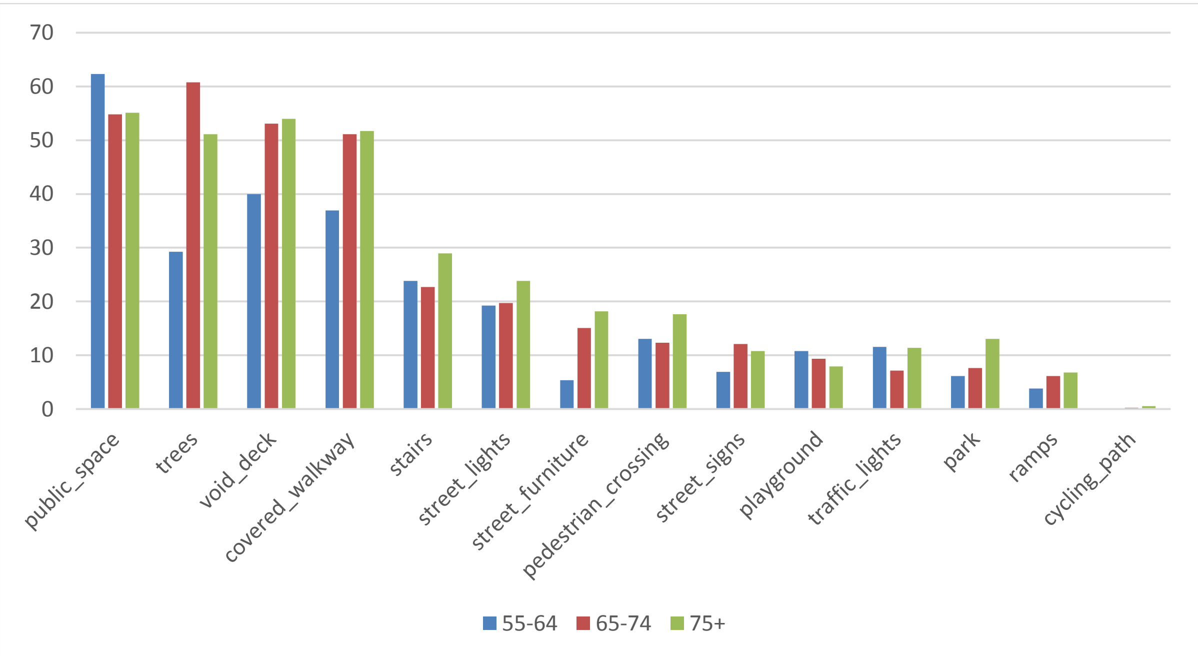

Figure 4 Percentage distribution of built environment features encountered during walking trips by age groups

4.4 Destination choices of walking trips

Using the 730 walking trips identified for the 30 participants over 175 days, frequent destination choices were identified by calculating the percentage of each type of identified destination locations in the total number of walking trips undertaken by the participants. The results are indicated as follows.

1) Overall distribution

Figure 5 shows the distribution of walking trip destinations by percentage among the participants. Void decks and public open spaces ranked first (approximately 13.8%) and fourth (approximately 7.9%) in terms of the percentage of destination choices among all walking trips that are not homebound. This is not surprising as both void decks and public open spaces are important and easily accessible shared common spaces in the neighbourhoods for older people to gather. Specifically, some void decks also provide senior activity corners that include public furniture and even kitchens, which provide a popular "hang out" place for older adults as well as venues for community activities (National Heritage Board, 2013).

Food courts ranked second among all the potential destinations (other than home) by walking, possibly as they provide a common area for daily self-served meals at affordable prices as well as a place to meet and see people and activities. Senior activity centres is the third top destination that older adults regularly walk to among all non-homebound trips. Those centres are common near-home spaces in Singapore's public housing, usually located at void decks and providing recreational facilities, activities, and exercise programmes for older adults to 'drop in' and engage in social activities (Health Hub Ministry of Health Singapore, 2020). Other places that older people more frequently walk to include shops and bus stops. While shops meet older adults' daily needs such as grocery shopping, bus stops may function as an intermediate destination for older adults to undertake long-distance travel and access further amenities by bus.

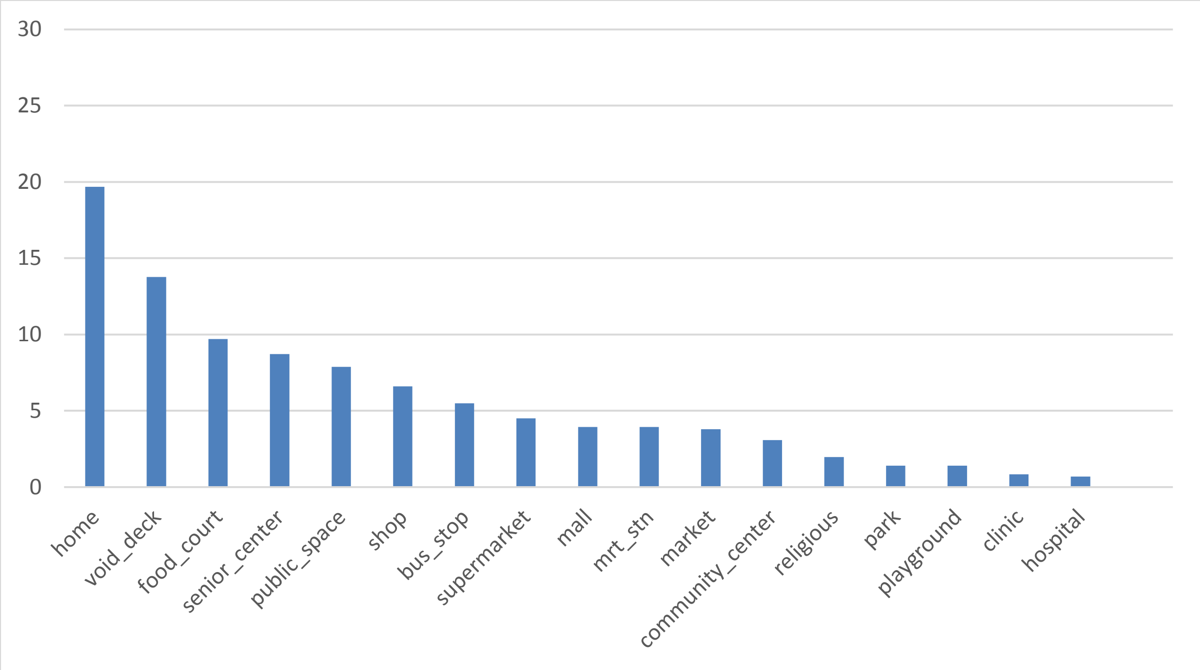

Figure 5 Percentage distribution of walking trip destinations

2) By Gender

Figure 6 compares the differences of walking trip destinations between males and females. The results of Fisher's exact tests reveal that there is no significant relationship between gender and the choices of most of the walking trip destinations, except two, i.e., senior activity centres (p=0.002) and religious establishments (p=0.001) (see Table a4 in Appendix II). Older males seem to walk to these two types of places more frequently than older females in their daily lives. Specifically, the percentage of walking trips ended at senior activity centres for older males (approximately 13.2%) is more than twice of that for older females (approximately 6.3%). This result, however, differs from the findings of previous study that positive associations between social health and living proximity to senior activity centres was observed for older females but not older males, implying that older females seem to be more likely to participate in organized activities (Lane, Hou, Wong, & Yuen, 2020). However, given that we have an unbalanced sample by gender, further research is needed to confirm whether and to what extent senior activity centres play different roles in older males' and females' daily lives.

There is also a weak relationship between gender and the choices of supermarkets (p=0.075) and wet/dry markets (p=0.085) as walking destinations. The frequency of walking to these two types of places for older females is 2-3% higher than that for older males, which possibly reflect female roles in the family as main decision-makers of grocery shopping (Nielsen Global Connect, 2020). This finding is also consistent with the conclusions of Lane et al.'s study (2020) that proximity to markets are associated with better social health status for older females but not older males, possibly because older females are likely to frequent those places for daily shopping purpose more often than their male cohorts, thus having more chances of engaging in unplanned social interactions such as casual chitchat and negotiations over price and products.

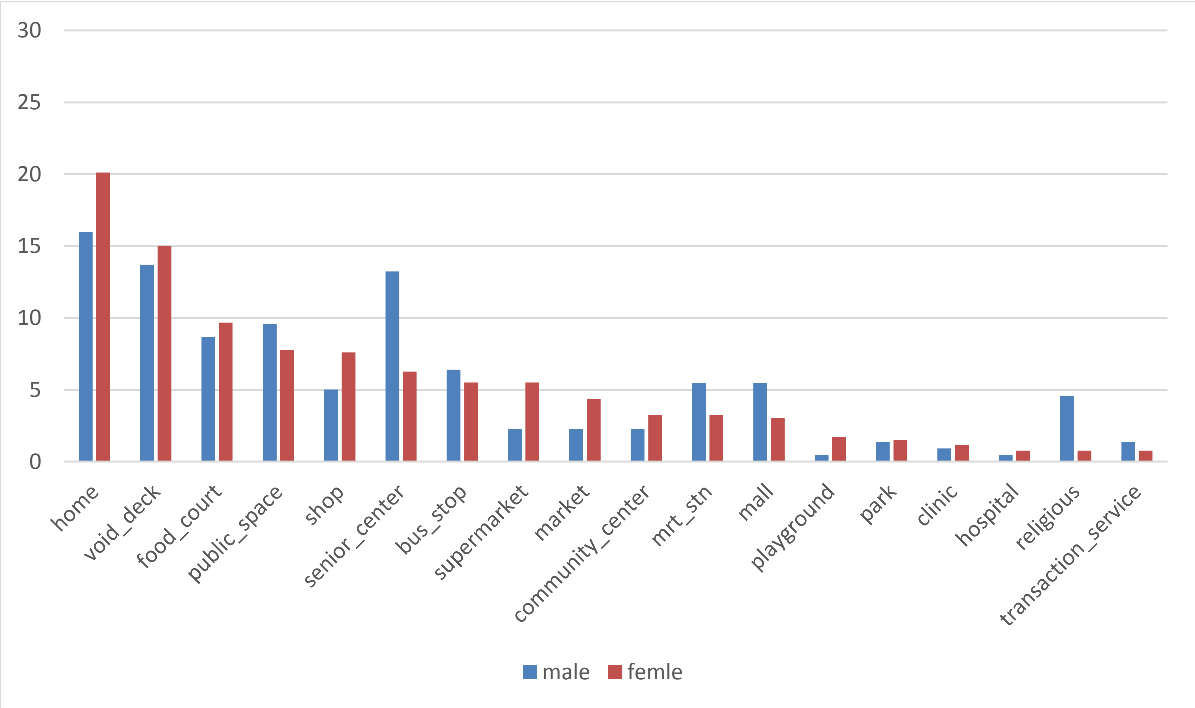

Figure 6 Percentage distribution of walking trip destinations by gender

3) By Age Groups

Figure 7 presents the distribution of walking trip destinations by age groups. All three age groups show different trends in terms of the propensity of choosing most of walking trip destinations, mostly in two types of places: senior activities centres (Fisher's exact test: p=0) and religious establishments (Fisher's exact test: p=0) (see Table a4 in Appendix II). More than 14% of the walking trips undertaken by those aged 75 and over ended in senior activity centres, while about 8.4% of the walking trips by those aged 65-74 is directed towards the centres. By contrast, those aged 55-64 rarely walk to senior activity centres. This implies that senior activity centres are likely to play more important roles in the daily lives of older adults who are beyond retirement age and have more leisure time. Whether the propensity of regularly visiting senior activity centres to engage in organized activities increases as people aged is an interesting question to be explored in future studies.

Moreover, the results of Fisher's exact test indicate that there is a weak relationship between age groups and the frequency of walking to void decks (p=0.09). The percentage of void decks in the total number of walking trip-making is highest among those aged 65-74 (16.5%), followed by those aged 55-64 (13.9%), and lowest among those aged 75 years and over (10.9%). Given that more than half of our participants belong to the young-old group, however, the differences across age subgroups in the demands of void decks for maintaining community ties in daily lives also deserves to be further explored in the future.

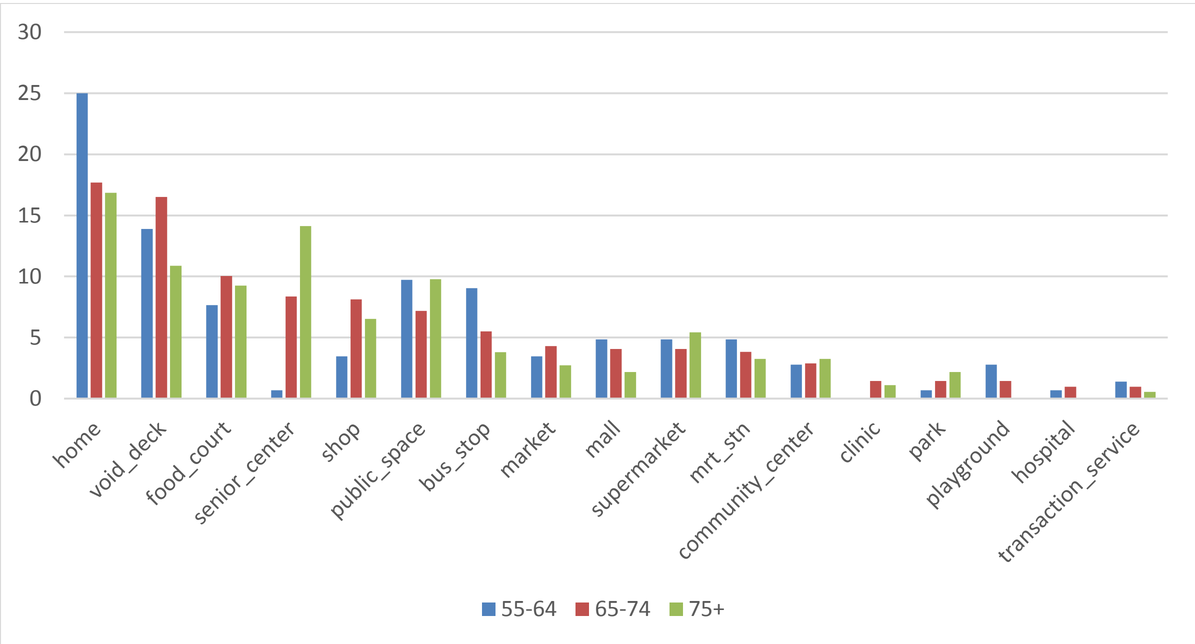

Figure 7 Percentage distribution of walking trip destinations by age groups

4) By time intervals of duration per trip

Figure 8 shows the distribution of destinations choices for short-duration, medium-duration, long-duration walking trips. Except the choices of religious establishments (Fisher's exact test: p=0.017), no significant relationship have been detected between time intervals of duration per trip and the choices of other types of place as walking trip destinations (see Table a4 in Appendix II). Given that more than half of the walking trips are within-10 minutes, this finding again reinforces the importance of bringing amenities and facilities closer to residents, especially those types of places that are closely related with local residents' daily needs.

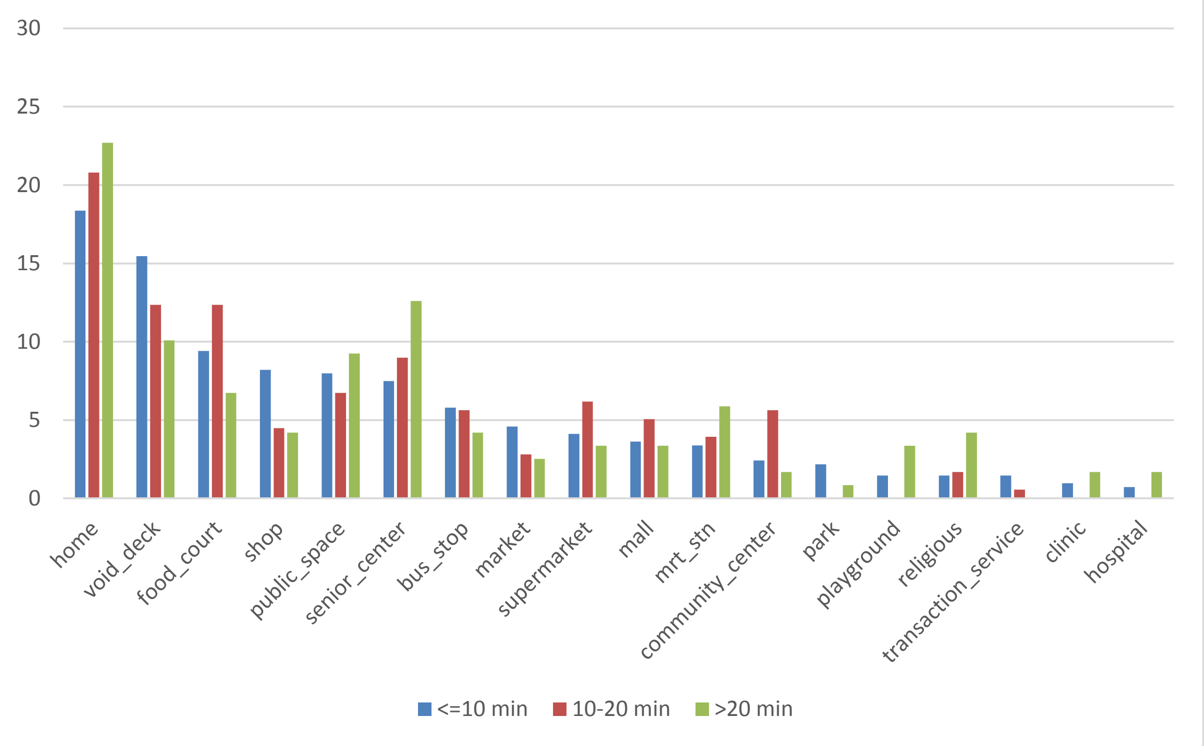

Figure 8 Percentage distribution of walking trip destinations by duration intervals

5. Conclusion

This study utilises visual lifelogging technique to collect information on older adults' daily walking experiences. We apply behavioural and environmental features coded from the lifelogging images to understand older people's walking travel and how they interact with and utilise the built environment features when they walk. The lifelogging images give a real-time glimpse of what the participants see/interact with as they move through their built environment even though more research is needed to understand why certain built environment elements are favoured or not.

The results indicate that older people in the three study neighbourhoods, on average, take about 4 walking trips per day, with each trip lasting about 14.5 minutes. There is no significant difference in the daily walking trip frequency of male and female older adults, nor any significant gender differences in walking trip duration. The differences in the amount of walking trips across age subgroups is not significant, either. However, the average duration of walking trips tends to decrease with age; walking trips of those aged 75 years and over is significantly shorter than the emerging-old by 3.7 minutes, implying that the age of 75 may be a threshold at which older adults significantly reduce the length of walking per trip while maintaining the frequency of walking trip-making per day.

We also observe that the distribution of daily walking trip-making among short-duration (<=10 minutes), medium-duration (10-20 minutes) and long-duration (> 20 minutes) is on average, approximately 2:1:1 and the distribution pattern of walking trips by duration intervals is consistent across all age and gender subgroups. In other words, older participants, on average, attribute more than half of their daily walking trips to short-duration ones (i.e. within 10-minute). This result implies the importance of providing daily goods and services such as food, groceries and leisure activities within a 10-minute walking distance of older adults' neighbourhood to facilitate their everyday outdoor lives.

In terms of route selection, participants in the three study neighbourhoods frequently passed through public open spaces, void decks, covered walkways, and places with trees when they walk. Interestingly, we find the young-old and old-old residents are much more likely to encounter street/pedestrian infrastructure that provides shade/shelter than the emerging-old residents. These facilities include void decks, covered walkways and spaces with trees, implying that the comfort and pleasantness of walking is perhaps more of a concern among those more senior older residents who have stepped into their retirement stage and thus, are more likely to have a flexible time schedule to choose the routes. We also observe that those more senior ones, especially those aged 75 years and over, are more likely to choose routes with street furniture, which would provide resting places for them.

In terms of destination choices of walking trips, void decks, senior activity centres, public open spaces, food courts, and shops are the five most visited destinations among all non-homebound walking trips taken by the participants. The first three destinations are shared common places for people to meet and engage in recreational activities such as chatting, engaging in exercises, playing mah-jong or chess (Aw et al., 2017; Wong, Lee, James, & Jancey, 2019). The destination choices match the findings from time diaries of 56 older adults in Singapore that found that the most frequently performed activities by older adults in Singapore are, apart from utilitarian activities, exercising and meeting family/friends or leisure activity (Krishnasamy, Unsworth, & Howie, 2011; Wong et al., 2019). We also observe that senior activities centres are most often visited by the old-old, followed by the young-old, but are rarely visited by those aged below 65. On the other hand, food courts and shops are essential facilities that local residents frequently walk to for daily food and grocery shopping.

In sum, reviewing real-time images could suggest to planners the type of places – destination choices, pedestrian infrastructure and built environment features to consider when planning for the older population's active and healthy ageing. Compared with other objective measures of built environment (e.g. GIS-based measures), the rich information provided in the lifelogging images allows us to extract nuanced design features such as tree shades, street furniture, and stairs that people are likely to interact with during walking trips. Moreover, short-duration walking trips (e.g. within 10-minute) walking trips that are easily ignored in previous survey-based analysis of travel/physical activity behaviour are allowed to be identified here, which would add to our understanding of walking behaviour.

Our results reinforce that certain types of places – public open spaces and senior activity centres are more frequently used by older residents while specific built environment features, e.g. covered walkways, trees, and street furniture are associated with older adult's trips. It is likely that these features facilitate a more comfortable, safe and interesting walking experience among older adults, especially those more senior ones. It further reiterates the need for neighbourhood design to take into account the various walking habits and needs of subgroups of older residents, as older adults are not a homogenous population. This study provides insights into the revealed walking patterns of older adults in Singapore and is a good starting point for planners to understand the environmental features and destinations that are frequently encountered and used by older adults.

5.1 Further Research and Limitations

As far as we know, this is the first study in Singapore to apply the visual lifelogging method to objectively record and assess older adults' daily walking pattern and real-time experiences with the built environment. The technology and techniques for the lifelogging camera device and image analysis are still under development. This development has influenced our data collection and data processing. First, we only include a convenient sample of 30 participants in three neighbourhoods of Singapore. The sample size was proposed based on suggestions of existing studies applying visual lifelogging, as well as considerations of time and monetary budget constraints for data collection, processing and coding. Additionally, despite extensive recruitment effort, it was challenging to recruit a larger sample size. We also observed that the three study neighbourhoods were relatively homogeneous in spatial characteristics as they were developed according to the public housing model of new town and neighbourhoods (Housing Development Board, 2020). This may have led to content saturation of images as similar built environment characteristics emerged repeatedly. Many previous studies have questioned the validity of applying passive photography for large-scale analysis (Kelly et al., 2011; Kelly et al., 2013), presenting a future research opportunity to explore the use of lifelogging cameras on different scales.

Second, we developed a coding framework that focuses on a limited number of features of the built environment, such as street furniture, covered walkways, ramps, and other street/pedestrian infrastructure that are important to walking. As urban contexts and activities differ, the coding framework may be improved and adjusted for different urban contexts and activities. The manual labelling process is time consuming and costly to implement, which also limited the application of the technology in travel behaviour analysis. Future development of machine learning algorithms to treat image data automatically might allow us to more efficiently identify and classify the travel and environmental features from those images, thus speeding up the processing and analysing of image data for travel and health-related research. The rich database for annotated images from an egocentric perspective built up in this study may provide a benchmark for future development of deep learning models of wearable based human activity recognition, especially in the context of Singapore.

Third, admittedly, the lifelogging camera might have led to adaptations in participants' behaviour, both intentionally and unintentionally (G. Wilson, Jones, Schofield, & Martin, 2016). Users of wearable cameras sometimes do not wear the camera in anticipation of non-users' reaction and looks. For this research study, we advised participants on how to explain the research study to non-users and offered to delete any photos of non-users. Even so, this might not have prevented such adaptation of behaviour. Participants might also be concerned about damaging the camera when engaging in physical activity and might not have worn the camera as a result.

Fourth, further research is needed to understand whether the revealed behaviour of participants' walking pattern matches their preferences. While this study found that certain environmental features and destinations are more frequently associated with older adult's walking patterns, this does not necessarily match their preferences. Older adults might have preferred destinations that are no longer accessible to them due to their reduced life space area (Hou et al., 2020; P. P. Koh, B. W. Leow, & Y. D. Wong, 2015). As a result, some preferred destinations might not have been captured in this study. The images also do not reveal preferences that are outside of existing facility provision and further research is needed to better understand these preferences and support ageing in place.

Appendix I: Passive Photo Capture Activity Briefing for Participants

You are invited to wear the lifelogging camera - Narrative Clip 2 as you go about your daily life activities over a period of one week.

1) **Activity duration:** 1 week

2) **When to wear the camera?**

Kindly remember to wear the camera every time you step out of your house.

3) **When not to wear the camera?**

- Kindly do not wear the camera in places that require privacy or security e.g. washroom, swimming pool, bank, airport and so on.
- Kindly do not wear the camera in any situation where it is attracting unwanted attention, or you feel threatened (Kelly et al., 2013).
- Kindly protect the camera from water.

4) **Downloading the photos**

At the end of each day for 7 days our research team will visit you at your residence to download the photographs from the passive camera.

5) **Reviewing the photographs**

You will be asked to review the photographs with the research team and provide information about your travel journey that morning and afternoon as shown in Tables a1 and a2.

Table a1: Travel Diary template of Day 1

Trip No.	**Which place did you visit this morning?**	**How did you travel to this place this morning?**	**Did you meet and talk to anyone during the trip?**	**Any additional comments**

Table a2: Travel Diary template of Day 2-7

Trip No.	Which place did you visit this morning?	Is this a new place that you have not visited in previous day(s)?	How did you travel to this place this morning?	Did you meet and talk to anyone during the trip?	Any additional comments

Charging the camera

After reviewing the photographs, the research team will assist you in charging the camera to get it ready for use the next day. The camera will take approximately an hour to be fully charged. If the four lights on the camera are illuminated, then it is fully charged and you may unplug the camera from the power outlet. However, keep the camera faced down on a flat surface overnight (face up is to take photos). Alternatively, you may keep the camera connected to a power outlet until the next morning to avoid draining the battery.

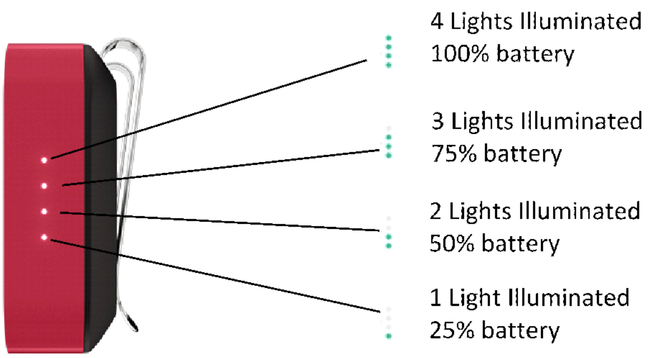

Figure a1: Charging the camera[12]

6) Operation of the camera

- Kindly note that the camera does not have any operational buttons.
- When charged and the camera lens is uncovered, it automatically captures photographs.
- When the camera is faced down or covered, it does not capture photographs.
- Kindly place the camera faced downward on a flat surface when not in use to avoid taking photographs and save battery.

[12] See http://start.getnarrative.com

[redacted]

Camera On **Camera Off**

Figure a2: Turning the camera on and off

7) Response to questions asked by a third party about:

- **Wearing the passive camera:** You can reply, **"**I am wearing the passive camera to help SUTD research team understand the user experience of my neighbourhood from an older person's point of view."

Deletion of third party photograph: You can reply, "I will inform the research team to delete photographs that include identification of the third party".

Appendix II

Participant ID	Image ID	Stamped Date/Time	Travel/ Activity	Environment features (examples)				Locations detected (examples)	
			Walk	Void deck	Open space	Furniture	Tree	MRT	Superm-arket
H13	1	10/01/2018 02:53	1	1	0	0	0	0	0
	2	10/01/2018 02:54	1	1	0	1	0	0	0
	3	10/01/2018 02:55	1	1	1	1	0	0	0
	…	…	1	…	…	…	…	…	…
	36	10/01/2018 03:17	1	0	0	0	0	0	1
	37	10/01/2018 14:04	1	0	1	0	1	0	0
	38	10/01/2018 14:04	1	0	1	0	1	0	0
	39	10/01/2018 14:05	1	0	1	1	1	0	0
	…	…	1	…	…	…	…	…	…
	71	10/01/2018 14:22	1	0	0	0	0	1	0
	547	11/01/2018 10:55	0	1	1	1	0	0	0

Figure a3 An example of output table for the information coded from the lifelogging images

Table a3 Results of Fisher's exact test on the relationship between gender/age groups and the presence of built environment features

Built environment features	Be gender	By age groups
Cycling paths	0.506	0.676
Street furniture	0.725	**0.002**
Parks	0.468	<u>*0.065*</u>
Pedestrian crossings	0.552	0.237
Playgrounds	**0**	0.685
Public open spaces	0.16	0.312
Ramps	0.487	0.537
Stairs	0.153	0.276
Street lights	1	0.483
Street signs	0.895	0.269
Traffic lights	0.568	0.133
Trees	0.118	**0**
Void decks	0.935	**0.022**
Covered walkways	0.119	**0.012**

Notes: <u>*Italic and underscored*</u>: $p<0.1$; **Bold**: $p<0.05$

Table a4 Results of Fisher's exact test on the relationship between gender/age groups/duration intervals and the choices of types of places as walking trip destinations

Types of places	By gender	By age bands	By intervals of duration per trip
Bus stop	0.593	0.373	0.966
Clinic	1.000	0.542	0.213
Community centre	0.636	0.955	0.165
Food court	0.782	0.910	0.500
Hospital	1.000	0.478	0.152
Mall	0.139	1.000	0.167
Market	<u>*0.085*</u>	0.163	0.594
MRT station	0.292	0.867	0.200
Park	1.000	0.269	0.115
Playground	0.170	0.243	0.154
Public open space	0.651	0.503	0.331
Religious establishments	**0.001**	**0**	**0.017**
Senior activity centre	**0.002**	**0**	0.227
Shop	0.409	0.145	0.298
Supermarket	<u>*0.075*</u>	0.640	0.723
Transaction service	0.429	0.760	0.742
Void deck	1.000	<u>*0.090*</u>	0.337

Notes: <u>*Italic and underscored*</u>: p<0.1; **Bold**: p<0.05

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