

Active travel: using wearable technology to analyse daily travel behaviour

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Abstract

Research findings from a wide range of health studies indicate that engaging in regular physical activity (PA) has positive effects on health outcomes. Travel, particularly commuting, consumes a significant proportion of the daily activity in which people engage. Driving, in general, is the least physically demanding travel mode and contributes to modern sedentary lifestyles and the associated health problems. Using public transport, as well as walking and cycling, provides opportunities for individuals to increase their levels of PA on a regular basis.

The goal of this exploratory study was to test and evaluate a unique combination of data collection instruments and techniques to gain an in-depth understanding of travel-related PA. This instrument 'kit' provided an accurate spatial and temporal account of daily activities, as well as supplementary contextual data (e.g. heart rate, conditions of the transport infrastructure and services, level of enjoyment) that are not commonly collected in travel and health studies. Participants in office-based (sedentary) occupations ($n=50$, data collection still underway) were asked to wear a Garmin smartwatch and EDESIX wearable camera (objective measures) and complete a self-report time-use diary for two days, followed by a reconstruction interview a few days later (self-report measures). The combined quantitative (GPS tracks, heart rate, PA, distances, activity duration) and qualitative (contextual information from the video footage and reconstruction interviews) data enabled us to cross-validate GPS and PA data with the diary reports, but also in order to better understand activity scheduling and travel mode choices.

1 Introduction

The benefits of active travel (AT) represent an important and timely research area, because decreasing levels of PA, particularly in developed countries, have led to rising levels of obesity and prevalence of chronic conditions such as hypertension, cardiovascular diseases, and diabetes (Loveday *et al.*, 2015; Götschi *et al.*, 2015; Mueller *et al.*, 2015; Giles-Corti *et al.*, 2016; Panter *et al.*, 2014; Stevenson *et al.*, 2016; Wang *et al.*, 2016). The benefits associated with regular moderate-to-vigorous physical activity (MVPA) are well-documented, and policy-makers across the world are applying these findings when implementing health-promotion programs.

A number of studies investigating (AT) report the positive effects of walking and cycling on physical health and life satisfaction, as well as associated environmental benefits (Saunders *et al.*, 2013; Mueller *et al.*, 2015). Consequently, many studies promote AT as part of daily commuting (Olsson *et al.*, 2013; Stevenson *et al.*, 2016) given that it is convenient and does not require people to devote additional time to PA during the day.

Transport researchers employ various technologies to investigate AT, such as GPS (Shen & Stopher, 2014a), mobile phones (Bierlaire *et al.*, 2013), wearable cameras (Kelly *et al.*, 2011; Doherty *et al.*, 2013; Shen & Stopher, 2014b) and pedometers and accelerometers (Steeves *et al.*, 2015), although few studies include multiple devices (Panter *et al.*, 2014; Kelly *et al.* 2015; Lee *et al.*, 2016; Voss *et al.*, 2016).

Some of the challenges associated with using multiple devices include participant burden, a paucity of literature addressing the complexities associated with merging and calibrating data from different sources, few 'proof of concept' studies, and a lack of researchers experienced in the emerging 'wearables' research field (Panter *et al.*, 2014; Handy & Davis, 2016). Moreover, there are relatively few multi-disciplinary studies because most of the research to date is specialised within transport, time-use, population health and the health sciences – each with well-established approaches to research design, methodology and analysis.

We argue that combining conventional diary methodologies with 'wearables' enables us to gain a substantially greater understanding and superior prediction of travel behaviour beyond the incremental additions of trip-chaining and GPS locations. Furthermore, passive data collection devices reduce respondent burden by shifting the 'load' to the analysts who integrate and calibrate these rich data sources. The reconstruction interviews bring insightful narratives on the circumstances and motivations for travel decisions.

2 Instruments and devices for capturing active travel

Activity-travel diaries and logs, with or without GPS tracking, have long been used for transport research (Ortúzar & Willumsen, 2011; Lee *et al.*, 2016). Self-report instruments (e.g. travel diaries, where the Origin-Destination (O-D) of each trip are included) often fail to provide detailed location information that is temporally valid or omit short trips and transfers. Furthermore, respondents often have incomplete spatial knowledge, tend to approximate durations and succumb to recall bias (Shen & Stopher, 2014a, b). For these reasons, we collected objective measurements using smartwatches and wearable cameras that could enhance, or even replace, conventional travel surveys.

2.1 GPS

GPS studies began in the late 1990s, but studies investigating free-living PA did not emerge until the mid-2000s. Although passive recording and spatial and temporal precision are the key strengths of GPS, they still have shortcomings such as data loss in certain environments (e.g. tunnels, indoor settings) or adverse weather conditions (e.g. cloudy or stormy weather). 'Priming' issues (the short delay before the GPS signal is captured and triangulation completed) and respondent protocol adherence are also persisting. As with most wearable devices, limited battery life can restrict data collection periods (Loveday *et al.*, 2015).

As devices are improving rapidly and offer more advanced location measurement systems and longer-life batteries, the feasibility of using GPS for transport and health

studies has increased considerably. Concomitant advances in data processing have made the calibration, synthesis and analysis of 'big data' more manageable.

GPS instruments have often been used in AT research, especially combined with travel diaries, in order to study how AT may help to increase commuters' PA levels (Mueller *et al.*, 2015; Voss *et al.*, 2016). Given that many people spend the majority of their time indoors, GPS carries limitations for AT research unless used alongside other devices, such as accelerometers or smartwatches.

2.2 Wearable cameras

Wearable cameras have been used in a number of research fields such as diet and nutrition (Gemming *et al.*, 2015), PA (Kerr *et al.*, 2016) and travel (Doherty *et al.*, 2013; Kelly *et al.*, 2013, 2015; Oliver *et al.*, 2010). They are worn by the participants on a lanyard or clipped to clothing, attached to a bicycle or rear-view mirror. Wearable camera images provide valuable contextual information, both indoors and out, in domestic, community and environmental settings. Camera footage provide clear evidence of sedentary behaviour (e.g. sitting in a bus or train) and PA (e.g. cycling or walking to work).

A few studies have combined wearable cameras and travel diaries to test the reliability of self-reported travel durations using objective image data. Kelly *et al.* (2015) found that wearable cameras provided more reliable data on the sequence of travel modes and duration than self-report accounts. The trip duration derived from the time-stamped wearable camera images suggested that participants overestimated their self-reported journey time (Kelly *et al.*, 2013, 2015). Wearable cameras (and to an extent, smartwatches) have removed one of the main concerns associated with accelerometry – the technical difficulties distinguishing the types and domains of PA (Carlson *et al.*, 2014; Loveday *et al.*, 2015).

2.3 Smartwatches

Smartwatches, now widely available and increasingly affordable, simultaneously collect and collate data on the wearer's heart rate (resting, maximum, mean), step-count, activity type, PA intensity, sleep duration and quality, and contextual variables such as location (GPS) and air temperature (Loveday *et al.*, 2015). As people become more familiar and comfortable with self-tracking using smartwatches and apps, participant compliance is increasing.

Smartwatches with GPS can be used to record total trip distance, duration, speed and calories/energy expenditure, which, in addition to heart rate, is considered sufficiently valid for analysis. Many health researchers choose GPS devices over heartrate (HR) monitors, as they are less prone to technical failure. Other limitations of HR monitors include higher hygiene requirements, wearer discomfort (e.g. skin irritation) and not being waterproof. The capacity for smartwatches to record weather related information (e.g. temperature and humidity) is also important for travel analysis, because active travellers appear to be more weather sensitive than their sedentary counterparts (Böcker *et al.*, 2016).

3 Sample and data

Data collection for this study is still underway; 50 participants have completed the two-day data collection. The volunteer sample includes 34 females, all in sedentary occupations, 43 living with somebody, and 21 with children still at home. Forty are

highly educated (at least a bachelor degree) and 41 reported good or excellent health (36 rated their health above their age group). Participants were free to decide whether or not to take part in the study, or to withdraw at any time, and provided signed informed consent. The research received approval from the UWA Human Research Ethics Committee, without any specific concerns on gathering video footage. At the end of the data collection period, participants were offered a gift voucher as a token of appreciation for their time (on average 1.5 hours interacting with the researchers, plus the two day of data collection period).

Four types of data were collected from each respondent: 1) quantitative self-report data from the time-use diary and a brief questionnaire; 2) quantitative information (HR, PA and GPS tracks from Garmin smartwatch); 3) video footage from the EDESIX wearable camera; and 4) qualitative data from the reconstruction interview. Images of the equipment used for data collection are presented in Appendix 1.

One of the main goals of the study was to cross-validate passive data collection devices with the self-report time-use diary. The incorporated GPS tracked participants' outdoor (and many indoor) locations and all travel episodes, whether active (i.e. walking or cycling), motorised (passenger car, taxi, bus or train) or multi-mode.

The Garmin calculates the total distance and duration of multi-mode trips, with the GPS coordinates, allowing different travel modes to be identified. As this model is water-resistant, many of the participants wore them continuously. One of the limitations of the Garmin is the requirement to activate the GPS manually by selecting a widget prior to undertaking the activity (e.g. walking, cycling), waiting for the GPS activation icon, then pressing start. A number of participants did not remember to do this for every trip, which resulted in missing data. Nevertheless, the available GPS location data were imported into Garmin Express for later analysis.

The video camera captured continuous footage from the wearer's point of view for all travel, but no sound was recorded (Figure A1). Some participants reported feeling uncomfortable wearing the camera on PT, but overall, compliance was high, with relatively little missing data.

Shortly after the data collection period (no longer than three days), participants were invited to a face-to-face 'reconstruction' interview. Before the interview, the camera data were downloaded into a proprietary Video Manager program. Before viewing the image data, participants were asked if there was any footage they did not want to share with the researcher. Then using the images as prompts, the participants described their commute and other travel episodes. The interview enabled participants to learn something about their daily activities and served as a cross-check for the diary and smartwatch data. Most of the interviews lasted about between 45-60min.

The data collection occurred over two consecutive weekdays, with a reasonably even distribution across the four combinations (i.e. Mon-Tue, Tue-Wed, etc.). Scheduling was quite complex due to the number of different work locations, part-time workers and limited research equipment. Each participant received in a research pack: an EDESIX wearable camera and quick-charge dock; a Garmin smartwatch and charging cable; a paper two-day time-use diary; a detailed information booklet and associated Quick Guide, summarising instructions for the devices. Table A1 (Appendix 2) includes some specifications for the devices, survey/diary instrument, and their features.

The detailed image data captured by the wearable camera during travel on public transport concerned some participants due to the lack of informed consent of other

passengers, particularly on trains, where seats face each other. The ease with which the research team could identify the participant's location (e.g. street signs, familiar shopping and recreation areas) was less of an issue, as the data were stored on a secure university server. We followed the comprehensive framework published by Kelly *et al.* (2013) on appropriate ethical protocols for using wearable cameras to meet the stringent requirements of the University Human Ethics Committee. Given that the cameras are fully encrypted, only the research team can access the recordings, and the footage used only for coding travel episodes and their attributes, no adverse/harmful effects to participants were envisaged.

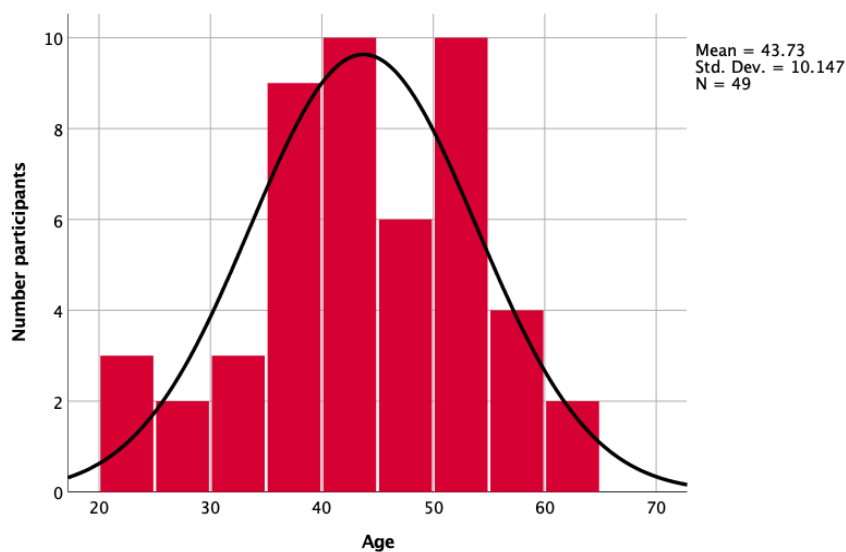
Finally, the research team recommended that participants check in advance that friends, family, and co-workers understood the nature of the study and were happy for them to take part and were advised of locations where camera may not be permitted.

4 Results

Given the complexity of the data and that the study is not yet complete, we report results from different data sources separately, without integration. Moreover, the data are collected at various temporal (e.g., heart rate each second, episode level for activities and PA; duration and energy level per activity or at daily and individual level) and spatial scales, so the results indicate different sample sizes.

To date quantitative personal data was coded for 49 respondents. The age distribution is bimodal (Figure 1), but without significant differences between males and females.

Figure 1: Age distribution of participants



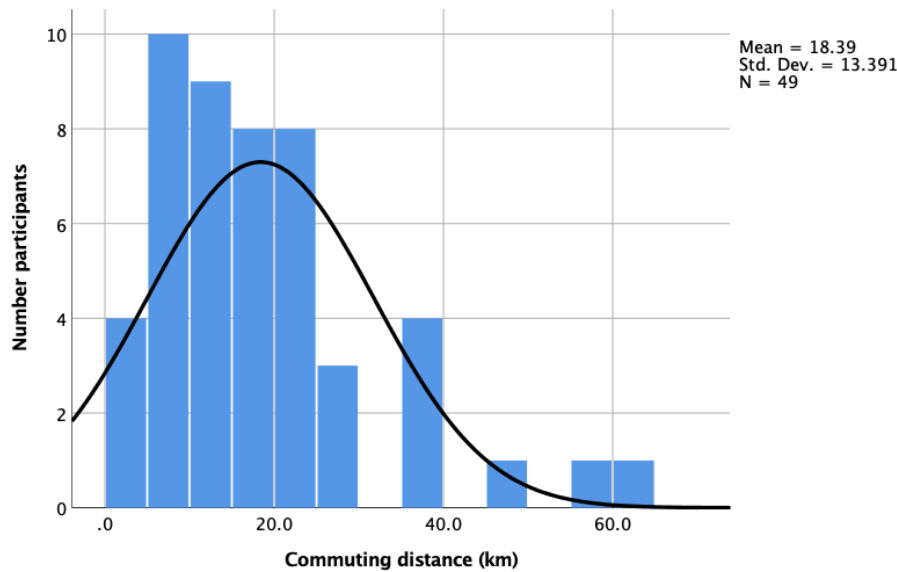
Five of the participants do not own cars and only four have working-from-home arrangements with their employer. Most of them live around 15km from workplace, with seven commuting over 40km (Figure 2).

In terms of travel mode, more than two thirds of the sample use bikes for some travel or recreation. The average travel distance per day was 35.6 km and the travel time 93.6 minutes, 80% of it allocated to commuting.

Given the sample size and study methodology, there is no inferential intent for the results. Rather, these results provide insights into factors influencing activity-travel

decisions and inform potential policies/measures aimed at promoting healthier travel solutions.

Figure 2: Distribution of commuting distance



In terms of travel, each respondent undertook one to three trip chains (sequences of trips in a tour that is direct to the destination or has intervening stops; they are defined for two anchors, home and work) per day, most of them home-based (N=28). Table 2 provides some descriptive statistics for the sample (N=37), while data collection is continuing. Half of the participants organised their daily activities in multimodal chains with an average of 3.74 legs, including 42% car travel, 10% PT, 30% cycling, and 18% walking.

Table 2: Sample statistics

Gender (% females)	69.4%	
Av. age (years)	43.73	10.15
BMI	24.83	3.71
Self-reported health status (1 to 5 scale)	4.10 (17 reported excellent health)	0.74
Av. distance home-work (km)	18.39 (males 22.31, females 16.82)	13.39
Part time workers (%)	20.4%	
Av. working hours/week	36.73	7.27
HR (beats/min) Garmin – range N = 37	80.16 (53 to 176, resting 61-70)	17.63
Av. travel distance/day (km/day) Garmin N = 37	35.6	12.77
Av. energy/day (kJ) Garmin N= 37	395	148.7
Car only travel (%)	32.6%	
PnR and KnR (%)	22.4%	
Public transport (%)	18.4%	
AT (%)	26.6%	
Duration travel-related PA activity (min) N = 143	20.19	
Duration travel episode (min) N = 247	22.98	7.80
Duration walking episode (min) N = 108	12.79	8.54
Duration cycling episode (min) N = 38	27.57	6.98

Enjoyment driving (reported, average) N = 77 (1=low and 7=high)	5.3	0.98
Enjoyment walking episodes N = 108	5.44	0.67
Enjoyment cycling episodes N = 38	5.46	0.55
Enjoyment PT travel episodes N = 24	5.75	0.82
Number of travel episodes/day N = 247	4.68	2.02
Duration travel/day (min)	93.59	38.61
Duration PT travel episode (min) N = 24	16.5	5.41

Note: The sample size indicates the number of episodes of various types accounted for in the currently coded data.

These preliminary results suggest that participants interested in the study (thus more active travellers and transport professionals) self-selected themselves and the average duration of various AT activities is higher than in the general population.

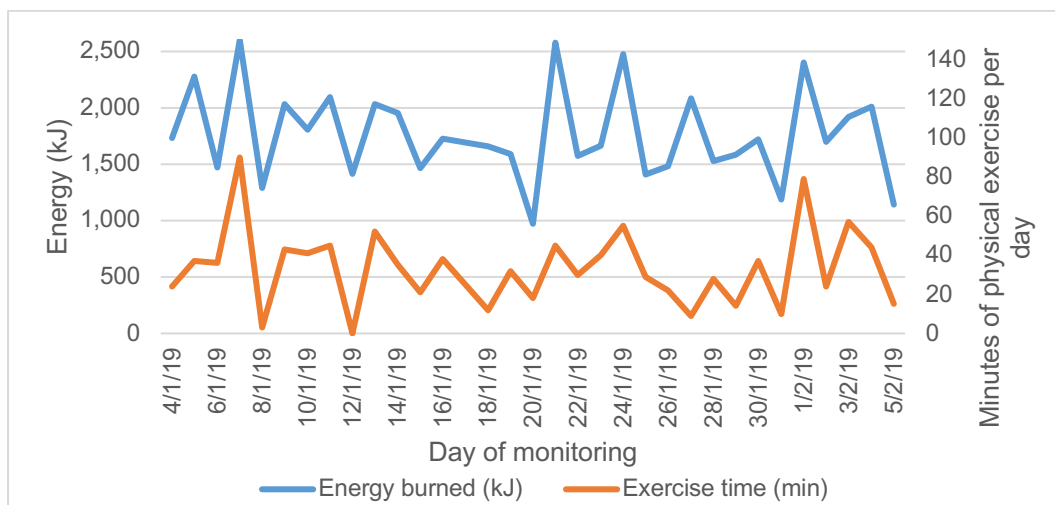
Although not tested statistically yet, the diaries showed substantial difference in the timing of activities (primarily due to the 5-min timeslots and rounding of durations in the diary) and omitted short trips (e.g., lunch break trips or to the local park) or transfers between modes of transport. We are still estimating the magnitude of these differences.

4.1 Garmin - heart rate data and GPS

The Garmin watches provided the total distance and duration of trips, with the GPS coordinates, allowing for different travel modes. As indicated, one of the shortcomings of the smartwatch was the requirement to activate the GPS by selecting a widget prior to starting the activity. Many respondents failed to do so for one trip, so not all movements have the GPS tracks recorded. For missing GPS, we imputed the routes using the camera data and comparing the derived distances and times with those reported in the time-use diaries.

Another important aspect of our data collection was the physical activity, measured in steps/distance, energy, and heart rate (HR). These are indicators used in PA research and our preliminary results showed significant correlations between the duration of PA episodes, energy expenditure (0.58) and HR (0.32) (see Figure 3).

Figure 3: Example of association between energy expenditure and PA duration



As shown in Table 2, the sample has a broad range of individuals with various fitness levels and BMIs. The average HR was 80.16 beats/min, and a standard deviation of 17.63 (N=37), confirming that several participants exercised during the two-day data collection.

Further demonstration of the differences in health/fitness indicators and AT is the significant difference between heart rate during travel by various modes. Table 3 shows considerably higher heartrate and number of calories consumed per travel episode if the individual walked or cycled, compared with driving and being a car or PT passenger.

Table 3: Sample statistics

Variable	AT		Not AT		p
	Mean	Std. dev.	Mean	Std. dev.	
Av. HR (beats/min)	97.00	15.07	70.98	17.54	<0.001
Calories	45.54	46.03	11.63	26.06	<0.001

The next step measure is to derive the heart rate variability (HRV), which is broadly accepted by health researchers as a good physiological indicator of autonomic nervous system activity and is being used routinely for modelling physiological stress and recovery reactions (Tonello *et al.*, 2014). Reduced HRV is considered a risk factor for negative cardiovascular outcomes, whereas higher HRV is associated with reduced morbidity and mortality and improved wellbeing and physical fitness (Tonello *et al.*, 2014). While the Garmin does not provide direct HRV measures, we derived this from the 1-sec recordings on the heart rate.

An example of HR data from a participant who has logged her PA with Garmin (in the Health app) is shown in Figure 4. Similar line charts are available for all other participants, although of a shorter duration and some with interruptions (when the widgets were not activated). These data are currently analysed and compared with the GPS tracks, an example of which is given in Figure 5.

Figure 4: Heart rate (beats per min) from Garmin

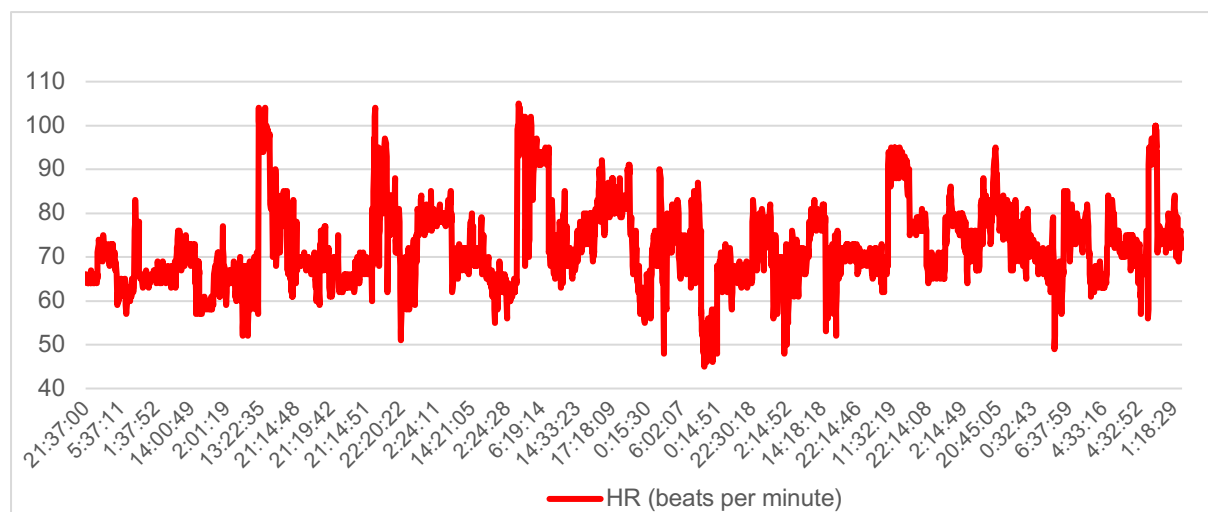
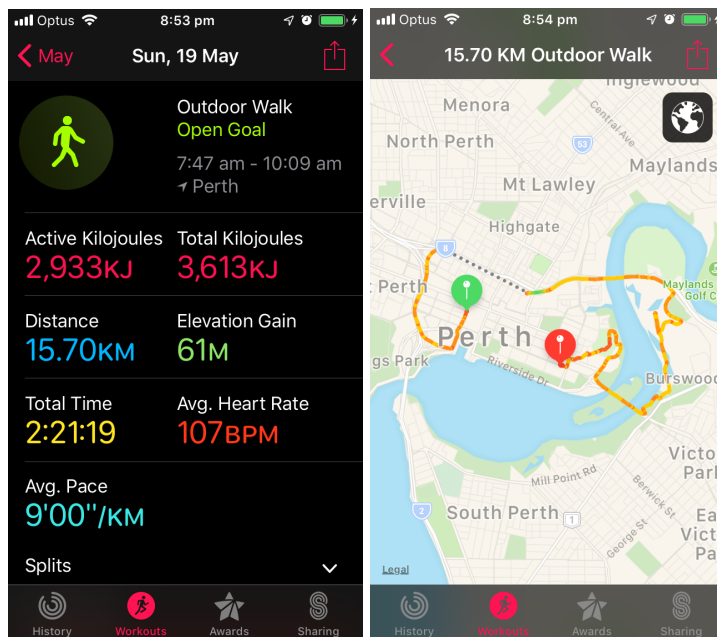


Figure 5: Example GPS track, heart rate, and energy expenditure from Garmin



4.2 Camera data processing

The big data revolution, accompanied by the development and deployment of many devices and mobile applications, as well as social media platforms, has enabled the research community to apply artificial intelligence (AI) and machine learning algorithms to vast amounts of data. One of the applications is pattern and video recognition (Zhou *et al.*, 2017; Monford *et al.*, 2019).

Modelling images is challenging even when using a 10-million places database (including people, places, objects, animals, and natural phenomena), as applied by Zhou *et al.* (2017) at MIT. However, capturing the change in scene/events poses additional challenges (temporal and auditory). Consequently, at the moment the research team is manually coding the segments and extracting information relevant to the project (quality of the amenity, traffic conditions, weather, etc.), while searching the possibility of future automated coding of the video material (Monford *et al.*, 2019). The footage from the respondents was split in scenes and images using an open source program (<https://github.com/krichter722/video-splitter>).

At the time of writing this paper, data are still being collected and coded. Preliminary results indicate a substantial underreporting of all activities, including trips (on average 2.82 fewer activities and 1.7 trips), but overestimation of the durations of the trips (4.59 min). Final statistics will be reported at the conference.

5 Findings

5.1 Qualitative interviews

The content analysis of the interview data (not included here) emphasises the predominance of car driving for home-based transport chains including commuting and that many participants escort children to day care and school before and after their paid work program.

Connections between various public transport modes and the access modes required careful scheduling of the daily routine and the quality of the infrastructure. Enablers or

deterrents from using AT, even as a part of a multi-chain trip using public transport appear to be associated with: the extent and condition of Principal Shared Paths (PSP) for cycling; shelters and information booths for PT; the design and aesthetics of the built environment (e.g., facades, limited foliage, lack of vibrancy) and; household characteristics (e.g. presence of children under 3 years in the family).

In general, the respondents were split into two main categories: PA enthusiasts, who use their commute or any travel as an opportunity to enhance their fitness and/or replace the need for PA activities during the non-work hours; and heavily-constrained travellers, many full-time employees working longer hours and completing longer trip chains, which included accompanying family members to their activities and household chores before and after work. Other comments focused on the perceived high cost of public transport and the availability of free or discounted parking, which encouraged car driving.

Overall, respondents reported that using the wearable camera was more 'demanding'/'challenging' than completing the two-day diary, and that activating the smartwatch was not straightforward, particularly waiting for the GPS signal.

5.2 Quantitative data

The results show that most participants' trips are multimodal, with trip chains including, on average, 3.74 segments. The mean travel distance is 35.6km and duration 94 min per day. The sample included individuals who are using more AT than the average resident in Perth, and less car-based travel (55%). The sample also included more females (70%) who travelled less km than males, but had comparable durations of AT.

Participants reported enjoyment of 5.43 (out of 7) associated with travel, exceeded by travel by PT, perhaps due to the simultaneous activities this enabled and the possibility of avoiding road congestion. The comparable enjoyment level for cycling and walking was lower than for public transport, because of the poor weather conditions many participants experienced during data collection.

The average duration of each cycling episode was 27.57 min, twice long as for walking. This is likely explained by the fact that many cycling episodes were door-to-door, while the walking trips were primarily for access and egress to PT.

When comparing the travel modes, considerably much higher HR and a higher number of calories was consumed per travel episode if the individual walked and cycled, as compared to driving, being a passenger in a car or public transport mode.

Our participants were relatively physically active, with an average daily energy expenditure of 395kJ, with the majority achieving the recommended 30 minutes of daily PA (150 min per week, as per the World Health Organisation, 2018).

Significant positive correlations were noted between the amount of AT (duration) and heart rate, which suggest that promotional programs should continue presenting the benefits of active travel.

In terms of validation, as expected, the camera and smartwatch (when GPS tracks were not missing) provided more precise and complete accounts of daily activities, including travel. More than half of the participants omitted activities from their time use diaries, including trips, which were captured in the video recording. Some disagreement was also found in travel durations and timing of activities. The main reason for the differences is the rounding to the nearest 5-10 min that affected both short and longer trips. On average trip durations were overestimated by 4.59 min.

Overall, caution should be exercised when judging these results, which are not representative for the population (self-selection bias) and incomplete.

5.3 Technology-related issues

Numerous respondents found activating the Garmin widgets when starting activities cumbersome, and as a result many travel-related PA information and GPS was missing from the Garmin dataset. Alternatives such as Apple Watch and Amazfit (<https://us.amazfit.com>), which are more passive and do not require participant intervention, could be tested. Both devices are waterproof, similar to the features of Garmin, and Amazfit has reported a longer battery life.

The VB-320 has a battery life of up to 8h, but the design consequence is a slightly bulkier camera body intended to be clipped to clothing, rather than worn on a lanyard – something that may deter some participants.

Other challenges refer to the relatively poor inter-operability between platforms, and some of the software does not allow direct raw data exports for further analysis (Garmin). This means that a larger time investment for analysis is needed. The other time-costly aspect involves the substantial and laborious manual coding required for camera data.

Regardless, it is our conclusion that the precision and enrichment brought by the combination of devices outweigh the costs, and that using combined research 'kits' should be an ongoing line of inquiry. However, current smartwatches and other recording devices cannot fully replace the traditional diaries. To address the issue of smartwatch widget activation, reminders as instant text messages may be considered in the future.

6 Discussion and conclusion

This paper reports on a pilot study that tested a combination of data collection instruments and techniques to understand travel-related PA.

As reported by Kelly *et al.* (2011) and Shen & Stopher (2014b), wearable cameras offer the closest alternative to direct observation for a wide range of travel scenarios. Objective assessment of travel conditions, locations, durations, as well as contextual information (e.g. traffic levels, infrastructure elements, environs, weather and light, vehicle occupancy or crowding) also inform decisions on the viability of alternative travel modes.

Another key component of the research 'kit' is making use of the smartwatch features – geocoding, monitoring steps and calories, HR, sleep duration and quality – all of which are associated with wellbeing. This exploratory pilot study shows that AT (even as part of multimodal PT travel) could be promoted as a PA intervention for at least some commuters. This can work in conjunction with other beneficial practices (e.g., nutrition, Ride-to-work Day, etc.). In addition to continuous monitoring, smartwatches provide immediate feedback and reporting for wearers (e.g., daily steps, calories, attaining a fitness goal) which may increase motivation and reinforcement for PA, as well as function as a reminder for maintaining healthy behaviour and practices.

Yet, participant compliance, cost, and specialised skills and substantial time for testing different techniques for harmonising different levels of analysis – spatially and temporally – are non-trivial aspects that call for additional research in this space.

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8 Appendix 1

Figure A1: EDESIX camera



Figure A2: Garmin smartwatch



Figure A3: Screenshot time use diary

Example

- Record your main activity for each 5-minute period. Only one main activity on each line!
- Distinguish between first and second job, if any.
 - Distinguish between travel and the activity that is the reason for travelling.
 - Don't forget the mode of transport or location and whether you were using a smartphone, tablet or computer.
 - Please remember to record who you were with.

Use an arrow or quote marks to record that an activity lasted longer than 10 minutes.

- For each 5-minute period, please write in how much you enjoyed this time on a scale of 1 to 7, with 1 meaning you didn't enjoy it at all and 7 meaning that you enjoyed it very much.
- For example, if you didn't enjoy an activity at all then you would write 1 in the box.

Time: 7am – 10am (Morning)					Were you alone or with somebody you know? Mark all relevant boxes				
Use an arrow or quotation marks to record that an activity lasted longer than 5 minutes									
Time: 7am–10am Morning	What were you doing? Please write down one main activity	If you did something else at the same time, what else did you do?	Used a smartphone, tablet, or computer	Where were you? Location, or mode of transport	Alone	Spouse/partner	Child aged 0-7	Child aged 8-18, or others	Others you know
7.00	Woke and dressed children			Home					
7.05	" "								
7.10	" "								
7.15	Had breakfast	Talked to family	✗			✗			
7.20	" "	" "	✗			✗			
7.25	" "	" "	✗			✗			
7.30	" "	" "	✗			✗			
7.35	↓	Listened to the radio	✗			✗			
7.40	Made lunches	↓							
7.45	" "	" "							
7.50	" "	" "							
7.55	↓	" "							
8.00	" "	" "							
8.05	Checked emails	↓	✗						
8.10	" "	" "	✗						
8.15	Packed bags	Called work	✗						
8.20	" "	" "							
8.25	" "	" "							
8.30	Left for the day care centre			Walk					✗
8.35	" "	" "							"
8.40	" "	" "							"

Figure A4: Additional kit (iWatch and Amazfit smartwatch)



9 Appendix 2

Table A1: Kit details and instructions

Device	Features	Instructions
Smartwatch Garmin VivoActive 3	Size: 43.4 x 43.4 x 11.7mm. Waterproof: Rated for swimming only. Screen: Sunlight visible, 1.2" diameter, 240x240px touchscreen. Battery life, GPS mode 13 hours; up to 7 days in smartwatch mode (with HR) 2.4 GHz @ 8 dBm nominal ANT+® wireless communications protocol Bluetooth® 4.2 technology	Start: Put the smartwatch on before you go to bed on the night before the first study day. Finish: Take off the smartwatch on the morning after the second study day. If possible, please wear all the smartwatch all day and night, even when showering or swimming (it is waterproof). If the smartwatch vibrates and says 'battery low', charge it for 10–15 min.

Device	Features	Instructions
	13.56 MHz @ -40 dBm nominal, NFC wireless technology (https://www.garmin.com/en-AU/)	A full recharge of the smartwatch requires 30 min (before the second study day).
Wearable camera EDESIX Video Badge (VB-200)	Size: 95mm x 62mm x 16mm Battery life, up to 48 hours in standby, 8-hours continuous recording Weight 137g with close-fit KlickfastTM Recording storage capacity: 16GB, 1GB at 640 x 368 standard resolution, 2GB at 1280 x 720 HD resolution Sealed unit with no user access to storage media or battery Download rate: 5min/hour of recording (parallel downloading with docking station); it requires high-speed Internet access Frame rates: 30/25/15/12.5 fps. By default VideoBadge records at 25 frames/s (https://www.EDESIX.com/downloads/spec-sheets/ED-002-002-02-VB-200-SpecSheet.pdf)	Start: Put on the camera when you are ready to leave for work in the morning of the two study days. Finish: Take off the camera when you have finished all travel at the end of each study day. To start recording, slide the thumb slider button, located on the right-hand side of the device downwards. To stop recording, slide the thumb slider upwards into its original position. The camera should record for 8-10 hours. If the power LED glows red/orange, the battery level is low. Using the quick charging dock (supplied), please give the camera a 'top up' charge for an hour or so.
Time use diary	Harmonised European Time-Use Survey (HETUS) Guidelines (Eurostat 2009) Two-day diary, 5-min time slot It records main/primary activity in which individual was engaging; any activities undertaken at the same time (secondary/simultaneous); who was present during this activity (co-presence) and; where the activity took place (location) or if travelling, the mode of transport Use of technology Level of enjoyment (scale 1 to 7, 1 meaning 'did not enjoy it at all' and 7 'enjoyed it very much').	Start: Start filling in the time-use diary when you first get up each morning on each study day. Finish: When you go to sleep at the end of each study day. Fill in the diary for the full two data collection days. Use an arrow to record activities that take longer than 5 minutes. Remember to complete all of the diary fields. Please indicate how much you enjoyed your time in various activities.