Journal of Transport & Health
Volume 30, May 2023, 101620

Demonstrating the applicability of using GPS and interview data to understand changes in use of space in response to new transport infrastructure: the case of the Cambridgeshire Guided Busway, UK

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https://doi.org/10.1016/j.jth.2023.101620

Highlights

- Using a natural experimental design we provide interpretations of possible effects of new transport infrastructure.
- Visualisation of GPS and accelerometer data show long episodes of physical activity accrued along transport infrastructure.
- Subject to residential urbanicity, a new active commuting route or space for leisure physical activity was provided.
- Two case studies showcase the combined use of GPS and interview data to understand how and why use of space changed.
- Studying how and why different groups respond to interventions contributes stronger evidence for equitable urban design.

Abstract

Introduction

Changes to the built environment can contribute to behavioural changes at the population level, including increases in physical activity. Evidence for how such interventions affect behaviour through qualitative understanding complements quantitative evidence of effectiveness of interventions, and may help to strengthen the basis for causal inference. We demonstrate the use of objective data to measure changes in spatial patterning of behaviour and physical activity in response to new transport infrastructure, as well as complementary interview data to understand why changes may have occurred. With a case study approach, we show how study design and a combination of data types can afford a stronger, more contextual package of evidence to meet methodological challenges of evaluating changes to the built environment.

Methods

Longitudinal questionnaire, GPS, physical activity monitor, and interview data from the Commuting and Health in Cambridge study (2009–2012) were used to understand changes in mobility and physical activity in response to an environmental intervention, the opening of the Cambridgeshire Guided Busway. Firstly, aggregate maps were derived to explore the spatial patterning of physical activity before and after the Busway opened. Secondly, changes in the size of activity spaces were described and associations with personal and environmental characteristics investigated to understand whose mobility patterns changed. Lastly, narrative data and maps of movement for two individuals as case studies were used to investigate mechanisms behind use of the intervention and related behavioural changes.

Results and conclusion

The Busway provided an alternative route for commuting, an additional space for leisure activity, and a new route for accessing greenspaces which may lead to potential changes in physical activity and wellbeing. Findings from studies which draw on multiple data types may be useful for informing the design and delivery of future public health interventions, an area where methods for evaluation and identification of plausible pathways to behavioural change remain underdeveloped.

Previous

Next

Keywords

GPS; Activity space; Natural experiment; Multimethod research; Causal explanation

Abbreviations

GPS, Global Positioning System

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1. Introduction

Changes to the built environment are increasingly being recognised as potential levers for behavioural change (Giles-Corti et al., 2016; World Health Organization, 2018). In the context of transport infrastructure, interventions that facilitate switching from private motor vehicles to alternatives may help to reduce traffic and air and noise pollution (Brook et al., 2010; Mills et al., 2015), and contribute to increases in overall levels of physical activity (Reis et al., 2016). To encourage the uptake of walking, cycling and public transport use and to realise positive health outcomes at the population level, policies need to be targeted and delivered effectively. As a consequence, there have been calls for a stronger evidence base to understand which types of built environment interventions are most effective and for whom, where, and why (Gelormino et al., 2015; Sallis et al., 2016).

Randomised controlled trials (RCTs), whereby individuals are randomly assigned to one of two or more groups of which only one is typically exposed to the intervention, have commonly been regarded as a reliable means for estimating impacts of an intervention. However, RCTs pose conceptual, ethical and practical difficulties for evaluating many policy or environmental interventions (Ogilvie et al., 2020). For example, it may not be practicable to randomise the implementation of some forms of new transport infrastructure that are developed in a specific location to serve a particular purpose. Elsewhere, it may be deemed unethical to deliberately withhold a new service that is already believed to be effective from a group of residents who already have knowledge of it. Consequently, natural experimental studies often provide a more appropriate alternative for exploring responses to changes in the built environment (Aldred, 2019; Leatherdale, 2019; de Vocht et al., 2021). In a natural experiment, exposures to changes are not deliberately planned or manipulated for research purposes but may be defined by time and place of implementation, providing more robust evidence for causal relationships than that obtained from non-experimental observation studies (Craig et al., 2012).

While natural experimental studies allow for evidence of effectiveness of interventions (*causal estimation*) to be developed, their design and conduct are often more complex and unpredictable than for a typical RCT. Interventions may be multi-faceted with multiple influences on behaviour which cannot be controlled for (Winters et al., 2017; Ogilvie et al., 2020), and identifying an association between an intervention and an outcome is not sufficient to prove a causal relationship. Combining evidence types to understand how interventions affect behavioural outcomes (*causal explanation*) may therefore help to strengthen the basis for causal inference (Victora, Habicht and Bryce, 2004; Aldred, 2019). This information, in addition to effect sizes, can ultimately deepen understanding of the most plausible and modifiable determinants of behaviours and health.

Global Positioning System (GPS) data are increasingly being used in place-based studies to measure environmental exposure, mobility and the spatial context of daily activities (Katapally et al., 2020). This highly granular location data can be useful for identifying the use of specific environments and changes in activity spaces and mobility patterns. Our recent literature review highlights the dearth of evidence using detailed geospatial data in evaluative studies (Smith et al., 2019). Elsewhere, qualitative data have been used to understand how spaces are used and the mechanisms behind their use. Linking qualitative and spatial data provides an opportunity to create geo-narratives: accounts of individuals' lived experiences based on a visual representation of the spatial context in which they occur (Kwan and Ding, 2008; Mennis et al., 2013; Meijering and Weitkamp, 2016). Geo-narratives can provide in-depth insight into individuals' geographies of mobility, including reasoning and perceptions around the navigation of physical spaces. Applied within an evaluative study, geo-narratives may provide greater understanding of whether, how, and why an intervention can bring about changes in behaviour.

In this paper, we aim to demonstrate the use of quantitative results alongside case study-based narrative data and visualisations of movement and activity. The purpose of the paper is to highlight the potential of combining and triangulating data types and approaches within a single study to generate evidence that may better inform interventions. We use the example of the Cambridgeshire Guided Busway and data collected as part of the Commuting and Health in Cambridge study in an effort to understand whether and how access to, and use of, an intervention may bring about changes in behavioural outcomes. Using combinations of GPS, physical activity monitor, and interview data, we focus on answering the following questions.

1) How does the spatial patterning of physical activity around the Cambridgeshire Guided Busway change in response to its opening?

2) Are personal and environmental characteristics, including proximity to, and use of, the Cambridgeshire Guided Busway, associated with changing patterns of mobility?

3) Can GPS and interview data provide insights into how and why individuals may have changed the spatial patterning of their behaviour post-intervention?

2. Methods

2.1. The intervention

The Cambridgeshire Guided Busway (hereafter referred to as the Busway) is a major transport infrastructure project comprising a bus network and an adjacent 22 km traffic-free walking and cycling route. The Busway opened in 2011 in Cambridge, UK (Fig. 1). Details on the development and study findings to date have been summarised elsewhere (Ogilvie et al., 2016).

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Fig. 1. Image of Cambridgeshire Guided Busway and map of off-road sections where path is located.

Cambridge has a number of major scientific and technology employers and the highest prevalence of cycling in the UK (Goodman, 2013; Ogilvie et al., 2016). The bus route was designed as an alternative to driving for commuters travelling into Cambridge and connects towns and villages to the north of Cambridge with employment hubs and the city centre. Buses run on a track segregated from traffic for the majority of the route and a path for pedestrians and cyclists runs alongside the Busway, creating a new space for active commuting and physical activity. Bus stops located close to park and ride facilities near St Ives and Longstanton also allow for individuals to incorporate physical activity into their route by parking at the facilities and walking or cycling the remainder of their journey.

2.2. Data collection

Data were obtained from the Commuting and Health in Cambridge study, a natural experimental cohort study conducted in four annual phases (Ogilvie et al., 2010). At all phases (Phase 1 in 2009 through to Phase 4 in 2012) participants completed a questionnaire assessing a range of individual, socioeconomic and household characteristics including use and awareness of the Busway. Phases 1–4 were temporally matched for each participant whereby data were collected in the same month of the year in all phases. For analysis in this paper, data from Phases 2 and 4 were used.

A sub-sample was invited to participate in objective activity monitoring in Phase 2 onwards, in which physical activity was assessed using combined heart rate and movement sensors (ActiHeart, CamNtech, Papworth, UK). The ActiHeart records a measure of physical activity energy expenditure in metabolic equivalents (METs) and has been shown to be a valid and reliable tool, particularly for measuring activities such as cycling (Brage et al., 2005). ActiHeart devices were set to record activity at 60s epochs. Members of the sub-sample were also invited to simultaneously wear a GPS device (QStarz BT-1000X receivers) which was attached to an elastic belt and worn on the hip during waking hours for 7 days in each phase. Participants were asked to recharge the battery for the GPS devices each night using a charger provided. At each phase, new cohort members were added to account for attrition. Repeat measures for Phases 2 and 4, required for analysis in this paper, were therefore available for only a sub-group of participants.

As well as objective monitoring, qualitative one-to-one interview data were collected for a sub-sample of participants. The original purpose of the interviews was to elucidate the influence of environmental and social factors on travel behaviour under different circumstances. Interviews were conducted between February and June 2013, after the Busway was opened. Interviews were semi-structured and questions asked related to experiences of using different modes of transport, and the facilitators of and barriers to travel behaviour change.

2.3. Preparing GPS data

The Busway opened in August 2011. To assess behaviours before and after its opening, objective data from Phases 2 (2010) and 4 (2012) of the study were used. It should, however, be noted that short sections of the Busway were accessible to pedestrians and cyclists at Phase 2, prior to the official opening. For each research question, participants were required to have complete questionnaire and GPS data at both phases. Details of the inclusion process are provided in Appendix A, Figure A2.

GPS data were prepared and cleaned in a four-step process (Appendix A) using ArcGIS Desktop (10.6) and Python. The process and variables used were informed by methods used in key literature (Tsui and Shalaby, 2006; Auld et al., 2009; Wolf et al., 2014; Sanchez et al., 2017) and tested and refined using raw data for a random 10% of participants in the potential sample.

Detailed information and justification relating to each step in the data cleaning process, including time and distance thresholds for identifying erroneous points, is provided in Appendix A, Figure A1. In brief, GPS points with systematic errors were removed first. These included points that were positioned outside of the study area, dated outside of the study period, and had incorrectly been attributed a speed of less than 0km/h. Next, significant jumps in distance and time between consecutive points were identified to detect and remove points incorrectly positioned due to signal stray and loss, and non-wear. Jumps were based on maximum possible car speeds (Appendix A). Total wear time for GPS devices was then calculated and days with fewer than 8h of wear were excluded.

Valid GPS data were used to derive outcomes for each research question. For research question 1, ActiHeart data points were matched to the closest recorded GPS point based on date and timestamp. Total wear time for combined wear of GPS and accelerometer data was calculated and participants were required to have at least three days of weekday and 1 day of weekend data.

For research questions 2 and 3, valid GPS point data were used to create different types of activity spaces, defined as locations encountered by individuals as a result of their daily activities (Appendix A). Based on the range of delineations identified in our recent review (Smith et al., 2019), two activity spaces were chosen. First, daily path areas were derived. GPS points were joined to create linear trajectories of movement which were buffered by 50m in order to capture key places visited by an individual, as well as immediate surroundings. Second, convex hull polygons, the smallest possible bounding box of an individual's GPS points, were generated to represent potentially accessible spaces based on the total extent of an individual's mobility. Analysis was performed for total week, weekday and weekend activity spaces. For weekday activity spaces, a minimum of 3 weekdays was required, and for weekend activity spaces, participants must have recorded at least 1 weekend day of data. Participants were included for analysis if they met the week, weekday or weekend criteria.

2.4. Analysis

Analyses were performed as part of an iterative process whereby the approach to each research question was informed by preceding findings. Results were then narratively drawn together to understand how the Busway was used, and to provide insights into why the spatial patterning of people's behaviour may have changed post-intervention.
RQ1: Spatial patterning of physical activity before and after the opening of the Cambridgeshire Guided Busway

Based on the value of METs recorded by the ActiHeart and assigned to each GPS point, a binary variable was initially created to indicate whether the participant was in moderate-to-vigorous physical activity (MVPA: above 3 METs) or not at each data point. Consecutive data points were then used to define episodes of MVPA. The number of minutes spent continuously above 3 METs in each episode was summed and attributed to each GPS point within the episode.

To map locations of aggregate physical activity, including the potential participation in physical activity along the Busway, matched GPS and physical activity data points from each participant were merged into a single dataset and then aggregated to create raster maps of physical activity for both phases. Over 3 million data points were available for Phases 2 and 4 combined. A cell size of 50m was used to capture the width of the Busway and minutes spent in an episode of MVPA was used as the input value and averaged for all GPS points within the same cell. Using a linear feature of the local route network, a 3D transect of mean time spent in episodes of MVPA along the Busway was created by interpolating cell values from the raster surface.

RQ2: Characteristics associated with changing patterns of mobility

All participants with valid GPS data points were included, and size of activity space was measured as the absolute area of each daily path area (km^2). Descriptive analyses were undertaken to assess the mean activity space size according to sociodemographic characteristics: age, sex, education, urban-rural status and car ownership at both study phases. Relevant questions from the survey that were applied within this study are included in Appendix B, Table B1. Two-sample t-tests and ANOVA were used to test for differences between outcomes at Phase 2 and 4 and sample characteristics.

To measure whether individuals' movement covered a larger or smaller area post-intervention, the activity space size measured at Phase 2 of the study was subtracted from that at Phase 4, converted to percentage change, and collapsed into tertiles of change. These tertiles corresponded with those who 'increased', 'decreased' or had 'no substantial change' in their activity spaces.

We used multinomial logistic regression models to assess the relationships between sociodemographic variables, proximity to the Busway, and categorical changes in activity space size. Key self-reported sociodemographic, contextual and travel variables were prioritised in univariate analysis: age, sex, highest educational qualification, car ownership, self-reported distance to work, urban-rural status of home address, and active commute to work (Appendix B, Table B1). Adjusted regression analyses included age, sex, and proximity to the Busway, as well as any additional variables significantly associated ($p<0.05$) with change in activity space size from the univariate regression model. These were combined in a single adjusted model.

RQ3: Individual profiles combining GPS and interview data

Six participants with valid GPS and questionnaire data also had qualitative interview data. New, continued, former, or no use of the Busway was determined for each participant using both self-report and GPS data (Appendix B). Subsequently, a purposively heterogeneous group of four of the six participants was selected to ensure a range in Busway users, change in activity space sizes, and proximity of Busway from home address.

A combination of qualitative and quantitative data was used to create individual profiles of four participants. Data included self-reported information on travel and Busway use, findings from the exploratory and regression analyses, detailed information from interview transcripts, and maps of GPS-measured mobility. Analyses were performed after data were collected, and map and interview data were triangulated for participants who recorded any Busway use by GPS (n=2). Individuals' daily path area activity spaces were visually inspected to identify which sections of the Busway had been accessed and a convex hull was displayed to visually demonstrate how specific trips can affect the size and shape of an individual's activity space.

The use of interview data was not intended as a formal qualitative analysis, rather a case study approach was used to provide context for quantitative findings and to identify potential ways the Busway was used and why, as well as possible mechanisms for changes in use of space (O'Cathain et al., 2010; Fetters et al., 2013). To guide the geo-narratives presented through the intersection of spatial and qualitative data, three topics were outlined a priori: i) how the Busway was used, ii) reasons for its use and non-use, and iii) how its use may relate to levels of physical activity. Relevant quotes were extracted from the transcripts, grouped by topic, and used to annotate two individuals' maps. Findings from the maps and interview quotes were discussed narratively by topic with a view to illustrating potential explanatory factors for changes in spatial patterns of behaviour.

3. Results

3.1. Samples

Data were provided by 444 participants at Phases 2 and 4 (full sample), of whom 78 (17.6%) had GPS data at both phases (potential sample). For research question 1, valid matched GPS and physical activity data were available for 53 participants. For research question 2, between 63 and 71 participants were included depending on number of weekdays and weekend days with valid data available.

The characteristics of the full sample, potential sample, and samples included for analysis in research question 2 are detailed in Table 2. The majority of participants included in the analytic samples were female (54%–58.2%) with mean ages of 44.8–45.9 years at baseline. Most of the included participants lived in urban areas and did not change home or work address between the phases, and only a small percentage did not own a car.

Table 2. Characteristics of participants with data collected at both Phase 2 and Phase 4 of the Commuting and Health in Cambridge study.

	Full sample		Potential sample		RQ2 Analytic samples					
	Data collected (n=444)		GPS data collected (n=78)		Whole week analysis (n=67)		Weekday analysis (n=63)		Weekend analysis (n=71)	
	n	%	**n**	%	**n**	%	**n**	%	**n**	%
Sex			*							
Male	**133**	30.0	**35**	44.9	**28**	41.8	**29**	46.0	**31**	43.7
Female	**277**	62.4	**43**	55.1	**39**	58.2	**34**	54.0	**40**	56.3
Age (in years)										
Mean (SD)	***45.6 (11.2)***		***45 (10.1)***		***45 (9.8)***		***45.9 (9.5)***		***44.8 (9.9)***	
<40	**141**	31.8	**24**	30.8	**20**	29.9	**17**	27.0	**22**	31.0
40–50	**125**	28.2	**26**	33.3	**23**	34.3	**23**	36.5	**24**	33.8
>50	**178**	40.1	**28**	35.9	**24**	35.8	**23**	36.5	**25**	35.2
Education										
Less than degree	**107**	24.1	**15**	19.2	**14**	20.9	**10**	15.9	**15**	21.1
Degree or higher	**303**	68.2	**63**	80.8	**53**	79.1	**53**	84.1	**56**	78.9
Car ownership			†							
None	**59**	13.3	**3**	3.8	**3**	4.5	**3**	4.8	**3**	4.2
One	**204**	45.9	**39**	50.0	**34**	50.7	**30**	47.6	**37**	52.1
More than one	**181**	40.8	**36**	46.2	**30**	44.8	**30**	47.6	**31**	43.7
Moved work										
No	**361**	81.3	**68**	87.2	**58**	86.6	**56**	88.9	**62**	87.3
Yes	**76**	17.1	**10**	12.8	**9**	13.4	**7**	11.1	**9**	12.7
Moved home										
No	**371**	83.6	**63**	80.8	**55**	82.1	**52**	82.5	**59**	83.1
Yes	**69**	15.5	**15**	19.2	**12**	17.9	**11**	17.5	**12**	16.9
Urban-rural status			*							
Urban	**301**	67.8	**43**	55.1	**39**	58.2	**35**	55.6	**40**	56.3
Rural	**143**	32.2	**35**	44.9	**28**	41.8	**28**	44.4	**31**	43.7

*p<0.01 †p<0.05 indicates significant difference between full sample and potential sample.

3.2. RQ1: spatial patterning of activity over time

In most areas where MVPA was recorded, episodes averaged less than 5 min. Fig. 2 shows the spatial distribution of MVPA in the areas around the Busway before and after the intervention. In Panel A, episodes of more than 10 min of MVPA were recorded at Phase 4 in the most northerly section and as part of a route accessible from the Busway south of Fen Drayton in a local nature reserve. Values along the Busway in the 3D transect (Panel B) represent episodes of MVPA at Phases 2 and 4, shown in blue and green respectively. The transect shows some data were collected along the Busway at Phase 2, indicating that select journeys were made along the path. However, as cycling was difficult and could only be done slowly before the official Busway opening, little or no MVPA is shown. In contrast, data at Phase 4 clearly show episodes of MVPA recorded along the whole length of the Busway which are consistently longer than those at Phase 2. The longest episodes of activity are recorded in the most northerly section which may be indicative of long cycling journeys starting or ending in Cambridge. Some of the bus stops appear to coincide with shorter episodes of MVPA which may be due to participants exiting or entering the Busway or slowing down for road junctions, capturing the start or end of an episode.

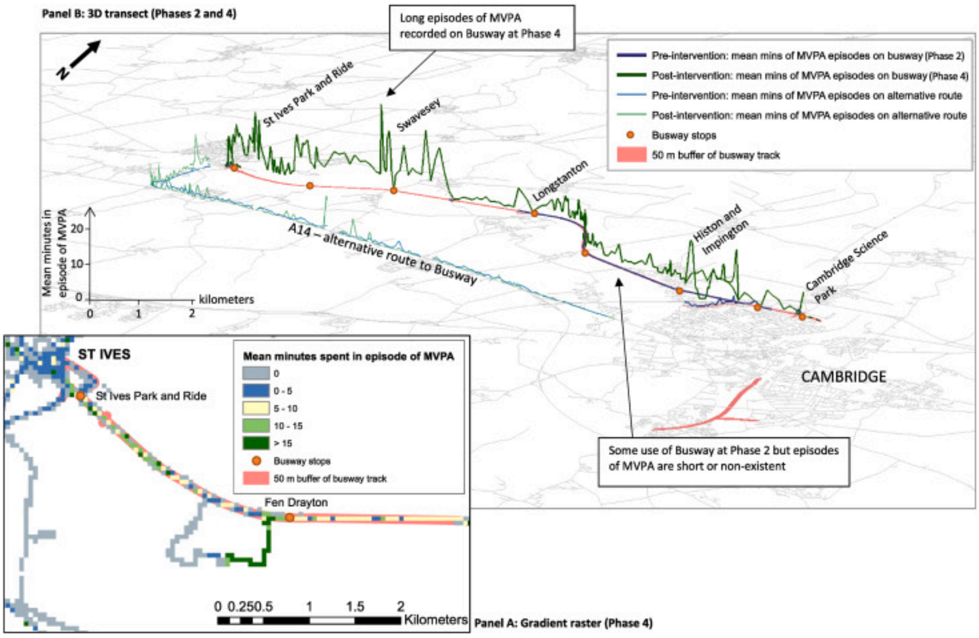

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Fig. 2. Point-to-raster gradient map and 3D transect of mean minutes spent in episodes of MVPA along the Busway.

Scales added in Panel B approximate for visual reference. Contains OS data

An alternative route along the A14, a major trunk road from St Ives to Cambridge, is illustrated for comparison in Fig. 2. Short or no episodes of MVPA are shown as expected for a route designed solely for motor vehicles. Some peaks indicating longer episodes do appear close to St Ives and at cross-roads, possibly capturing MVPA on routes that cross the A14.

3.3. RQ2: characteristics associated with changing patterns of mobility

Table 3 shows the mean activity space size according to sample characteristics at both phases, as well as the mean within-person changes. No significant differences in activity space size were found by age group, sex, or education. Urban dwellers had smaller activity spaces than their rural counterparts at Phase 4 for whole weeks and weekdays. Participants owning no car showed larger decreases in activity space size compared to those with two or more cars. However, there was only a small number of individuals within this stratum and the large effect size may suggest the difference was driven by a long weekend trip at Phase 2.

Table 3. Mean activity space size (km^2) by sociodemographic characteristics.

	Week			**Weekday**			**Weekend**		
	Phase 2	Phase 4	**Change between Phases 2 and 4**	Phase 2	Phase 4	**Change between Phases 2 and 4**	Phase 2	Phase 4	**Change between Phases 2 and 4**
	Mean (SD)	Mean (SD)	**Mean (SD)**	Mean (SD)	Mean (SD)	**Mean (SD)**	Mean (SD)	Mean (SD)	**Mean (SD)**
Whole sample	14.8 (12.5)	13.2 (13.2)	**−1.5 (15.8)**	8.8 (8.1)	9.1 (11.4)	**0.3 (12.6)**	7.5 (7.8)	6.1 (7.5)	**−1.5 (10)**
Sex									
Male	16.1 (16.1)	12.3 (11.3)	**−3.8 (14.9)**	9.2 (10.3)	8.9 (9.8)	**−0.3 (11.1)**	8.4 (9)	5.7 (6)	**−2.7 (9.2)**
Female	13.8 (9.2)	13.8 (14.6)	**0.1 (16.4)**	8.5 (5.8)	9.4 (12.8)	**0.9 (14)**	6.9 (6.8)	6.4 (8.6)	**−0.5 (10.6)**
Age [Years]									
<40	16.5 (15.3)	10.9 (7.8)	**−5.6 (15.3)**	9.5 (9.2)	5.0 (5.2)	**−4.4 (10.0)**	8.2 (9.3)	6.9 (7.2)	**−1.3 (9.3)**
40-50	11.8 (8.6)	15.8 (17.4)	**3.9 (18.2)**	6.3 (5.1)	11.2 (14.6)	**4.9 (15.8)**	6.7 (6.9)	6.6 (9.4)	**−0.1 (12.2)**
>50	16.1	12.71	**−3.4 (12.5)**	10.8	10.1	**−0.7 (9.3)**	7.8 (7.5)	4.9 (5.8)	**−2.9 (8.4)**

	Week			Weekday			Weekend		
	(13.1)	(12.2)		(9.3)	(10.9)				
Education									
Less than degree	13.8 (9.1)	10.8 (9.6)	**−2.9 (10.5)**	7.7 (4.2)	8.7 (6.8)	**0.9 (8.4)**	7.8 (7.1)	5.4 (8.2)	**−2.4 (10.3)**
Degree or higher	15 (13.4)	13.8 (14)	**−1.2 (17)**	9.0 (8.7)	9.2 (12.2)	**0.2 (13.4)**	7.5 (8.1)	6.3 (7.4)	**−1.2 (10)**
Urban-rural status		*			*				
Urban	13.7 (12.6)	9.9 (7.7)	**−3.8 (12.9)**	8.1 (7.1)	6.2 (5.6)	**−1.8 (8.7)**	7.2 (8.7)	5.3 (6.6)	**−1.9 (9.9)**
Rural	16.2 (12.6)	17.8 (17.5)	**1.7 (18.9)**	9.7 (9.3)	12.8 (15.4)	**3.1 (16)**	7.9 (6.7)	7.1 (8.6)	**−0.8 (10.3)**
Car ownership									†
None	22.6 (15.2)	4.4 (2.5)	**−18.2 (14.7)**	7.1 (4.5)	4.0 (2.3)	**−3.2 (6.1)**	16.7 (13.8)	1.9 (1.2)	**−14.9 (13.4)**
One	13.8 (11.0)	13.5 (15.4)	**−0.3 (17.4)**	7.0 (6.2)	9.8 (14.3)	**2.8 (13.7)**	7.9 (7)	6.1 (6.6)	**−1.8 (9.5)**
Two or more	15.1 (14.0)	13.8 (10.9)	**−1.3 (13.4)**	10.8 (9.7)	9.0 (8.4)	**−1.7 (11.8)**	6.3 (7.9)	6.5 (8.8)	**0.2 (9.6)**

**$p<0.001$ *$p<0.01$ †$p<0.05$ indicates significant difference between groups at each phase. Change is within-person difference in activity space size (km^2).

Adjusted associations of sociodemographic characteristics and exposure to the Busway with changes in activity space size are presented in Table 4. Those living further from the Busway were less likely to have increased their weekday activity space size than those living closer (relative risk ratio [RRR]: 0.49, 95% CI: 0.27, 0.86). This suggests that the change in spatial patterning of weekday behaviour was different for those more exposed to the Busway. Urban-rural status was associated with a change in activity space size at weekends. After adjustment for proximity to the Busway the association persisted, with rural dwellers less likely to increase their weekend activity space size compared with urban dwellers (RRR: 0.22, 95% CI: 0.06, 0.81).

Table 4. Adjusted associations between sociodemographic and geographic characteristics and exposure to the Busway with change in activity space size.

	Week		Weekday		Weekend	
	Decrease RRR (95% CI)	Increase RRR (95% CI)	Decrease RRR (95% CI)	Increase RRR (95% CI)	Decrease RRR (95% CI)	Increase RRR (95% CI)
Proximity to Busway						
(ref: closest)						
Furthest	0.94 (0.60, 1.46)	0.96 (0.61, 1.52)	0.72 (0.44, 1.18)	**0.49 (0.27, 0.86)***	0.75 (0.47, 1.20)	0.77 (0.48, 1.24)
Urban-rural status						
(ref: urban)	*n.i*	*n.i*	*n.i*	*n.i*		
Rural					0.41 (0.12, 1.44)	**0.22 (0.06, 0.81)***

Model adjusted for age, sex, and significant variables from univariate analyses. Bold text indicates statistical significance (**$p<0.001$ *$p<0.01$ †$p<0.05$). RRR – relative risk ratio; CI – confidence interval; n.i – not included in model.

3.4. RQ3: individual profiles combining GPS and interview data

Characteristics for each individual, their Busway use, and changes in size of activity space are shown in Table 5. Distance to work, usual commute mode, and proximity to the Busway varied across participants and participant 3 was the only person without access to a car. Use of the Busway was self-reported by both urban and rural dwellers and by participants with long and short commutes (participants 2, 3, and 4). In contrast, GPS-measured use of the Busway was only recorded for urban dwellers (participants 3 and 4), both of whom lived in towns outside of Cambridge.

Table 5. Characteristics and travel behaviours of participants included in qualitative analysis.

Participant ID	**1**	**2**	**3**	**4**
Characteristics				
Age (Phase 2)	63	31	44	42
Sex	Female	Female	Male	Female
Urban-rural status (Phase 2)	Rural	Rural	Urban	Urban
Moved home	No	No	Yes	No
Moved work	No	No	No	No
Travel options and behaviours				
Number of cars (Phase 2)	2	1	0	1
Number of cars (Phase 4)	2	1	0	1
Distance to work (Phase 2)	>20km	0–5km	10–20km	>20km
Distance to work (Phase 4)	>20km	0–5km	>20km	>20km
Usual active commute	None	None	Former	New
Proximity to Busway (Phase 2)	Close	Mid	Close	Far
Proximity to Busway (Phase 4)	Close	Mid	Close	Far
Self-reported measures of Busway use				
Use of Busway	None	New	Continued	Continued
Use of Busway for walking or cycling	None	New	Continued	Continued
Use of Guided Bus	No	Yes	Yes	No
GPS measures of Busway use and change in activity space features				
Week:				
Use of Busway	None	None	New	Continued
Change in activity space size	Decrease	Increase	Decrease	No change
Weekday:				
Use of Busway	None	None	New	New
Change in activity space size	Decrease	No change	Increase	Increase
Weekend:				
Use of Busway	None	None	None	Continued
Change in activity space size	Decrease	Increase	Decrease	No change

Maps of weekday and weekend activity spaces for the two GPS-measured users of the Busway (participants 3 and 4) are presented in Fig. 3, Fig. 4. The maps show the spatial patterning of movement at both study phases, and are presented alongside qualitative interview data to provide insight into how and why the Busway was used, and the effect of its use on activity spaces and physical activity. Drawing on the information shown in the maps and qualitative data, these three topics are subsequently discussed in greater detail.

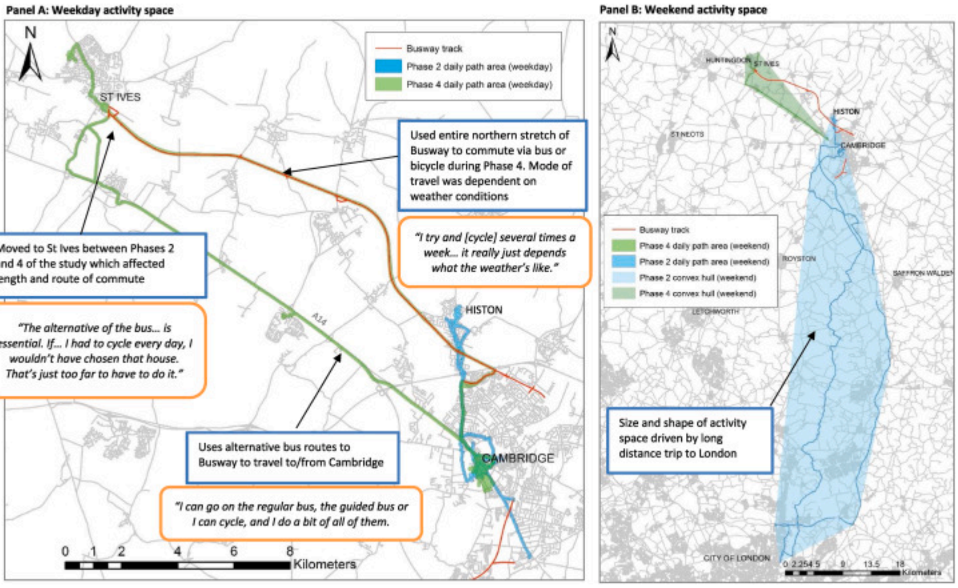

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Fig. 3. Maps of weekday and weekend activity spaces for participant 3 with quotes.

Explanation of visual output | Supporting quotation

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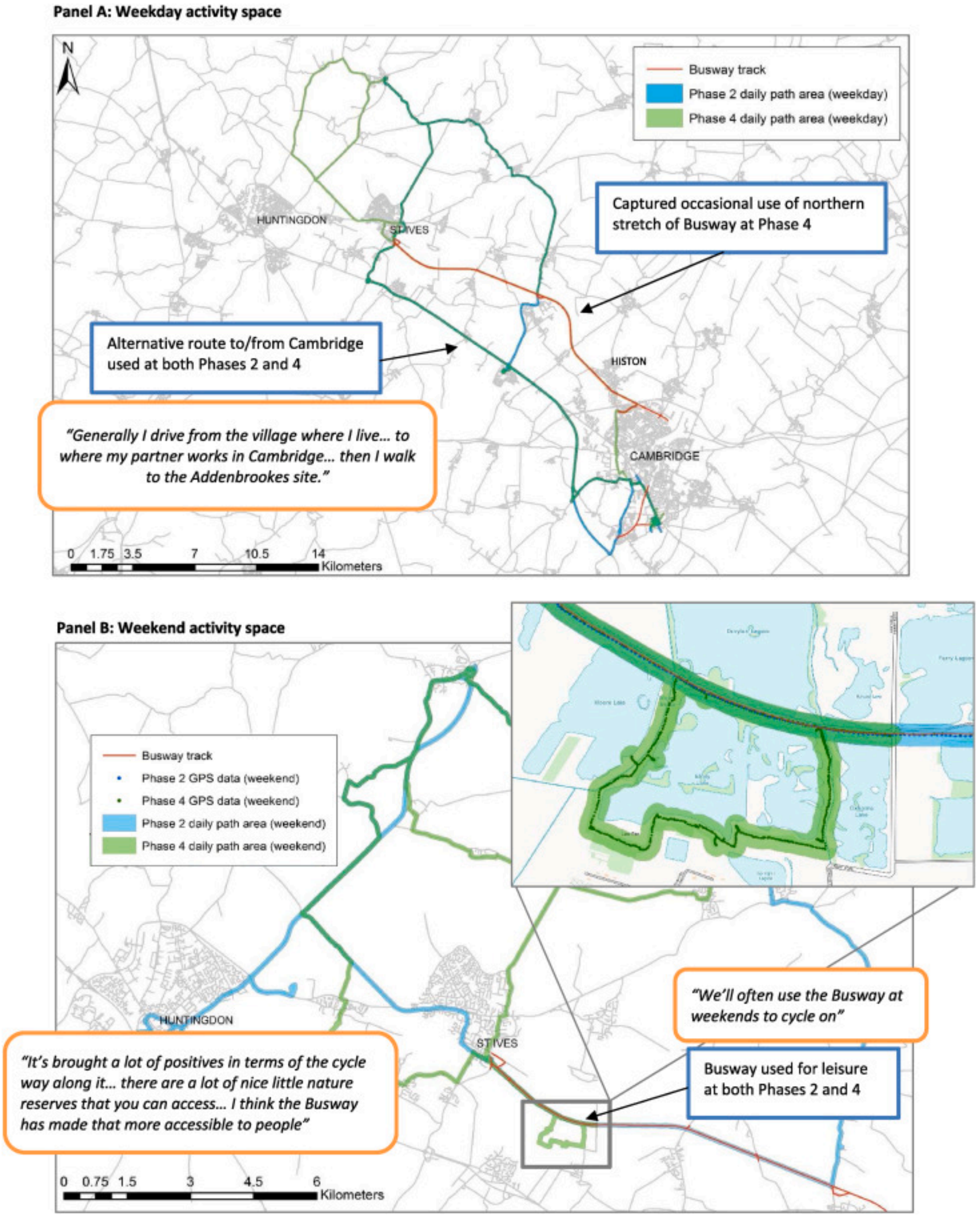

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Fig. 4. Maps of weekday and weekend activity space for participant 4.

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Topic 1: patterns of busway use

After its opening, the Busway was used as an alternative route for commuting by participants 3 and 4. Both the interview and GPS data show that a range of travel options between St Ives and Cambridge were both available and used. In Fig. 3, the weekday activity space after opening of the Busway captures participant 3's new commute route into Cambridge. They described how they switched between travel modes; travelling by guided bus or bicycle along the Busway, and using the "regular" bus to make the same journey along the A14 (Fig. 3). Participant 4 described how they typically drive into Cambridge during the week and occasionally use the Busway for active commuting (Fig. 4). This participant also described regular use of the Busway to walk or cycle for leisure at weekends, which is captured in Fig. 4 Panel B.

Although participant 2's activity space did not intersect the Busway, they reported new use of the Busway and guided bus since it opened. Participant 2 regularly commuted via motor scooter and similar to participant 4, described how they had used the Busway to cycle along for leisure.

"the Vespa is my main mode of commuting, particularly if I need to go into town … I have a wholly unsuitable bike for commuting … I have [used] the north route, and maybe cycled five miles … it's good to do time trials on it" [Participant 2]

Participant 1 reported and recorded no use of the Busway. They lived in a rural area, had two cars in the household and did not actively commute due to health reasons.

Topic 2: reasons for use and non-use

Weekday use of the guided bus was dependent on its convenience, with barriers to use, such as timing and busyness, contributing to use of local buses as an alternative (Fig. 3, Panel A).
"If you're at the Park and Ride and you try and get a bus at the Park and Ride at 7.30 in the morning, some of the buses are very full. And by the time they get to Longstanton … it has been known that there are people standing" [Participant 3]

The mode of travel used on the Busway appeared dependent on weather conditions and commuting long distances by bicycle was made easier by the availability of workplace shower facilities. The quality of the cycle path and directness of route was praised for being pleasant for cycling and reducing travel times. In Fig. 4, Panel B, participant 4's Phase 4 GPS trace showed a deviation from the Busway to local nature reserves. This participant welcomed the access to local nature reserves that the Busway provided, which they walked through at weekends after the Busway opened.
"The only reason I can [cycle] and do that distance is that we do have facilities at work … if there wasn't a shower there, I wouldn't even contemplate it." [Participant 3]

"It's a 50 mile round cycle ride so the weather conditions have to be perfect and I have to be full of energy … but it's really nice cycling along the Busway." [participant 4]

Topic 3: potential displacement and uptake of physical activity

Weekday activity spaces increased in size for participants 3 and 4, whose GPS data indicated new use of the Busway (Fig. 3, Fig. 4). However, there was no change to the size of participant 4's weekend activity space, as they used the Busway path before it opened in 2011 and continued to use the Busway for leisure at weekends afterwards (Fig. 4, Panel B).

The Busway therefore allowed for both active commuting and walking/cycling for leisure to be undertaken in a new space. Whilst the commute distances shown for participants 3 and 4 are likely too long to walk as the sole means of transport, the importance of physical activity and the possibility to incorporate mixed modes of travel into the commute along the Busway, including walking and cycling, was acknowledged.
"I use my commute as part of my exercise strategy, really. It saves me having to go to the gym. The gym's OK, but when the sun's shining I prefer to be out on my bike and exercising that way" [Participant 3]

4. Discussion

4.1. Study findings: building a narrative

The study demonstrated a proof of concept by illustrating a way to triangulate different types of data for a more complete picture of behaviour change in response to an intervention. Aggregate maps provided a first step in understanding how locations of physical activity changed, while individual-level and qualitative data allowed insight into who used the Busway, and how often, to be gained. Taken together, our data help explain how use of space for commuting and leisure changed after the opening of new transport infrastructure, the Cambridgeshire Guided Busway. We observed use of new infrastructure for physical activity with the potential to achieve long episodes of MVPA.

We found that those living in rural areas had larger weekday activity spaces, which were also less likely to change in size in response to the intervention, than with urban dwellers. Urban residents may be better connected to a range of different facilities and types of infrastructure and more likely to respond to interventions given shorter and more convenient travel routes. This is confirmed by another study drawing on this sample, which used self-report physical activity data and found that the effects of proximity to the intervention were stronger in those who lived in town or urban fringe areas (Heinen et al., 2014). Living further from the Busway was also associated with a lower likelihood of increasing the size of weekday activity spaces. Active travel has been shown to be less common in rural populations, and propensity to change travel patterns may be more limited given access and availability of safe active travel infrastructure (Hutchinson et al., 2014; Hansen et al., 2015).

The combination of GPS and interview data allowed for selected individuals' spatial patterning of movement to be explored in detail. As anticipated, we found that the Busway provided a new and favourable space for active commuting for residents in nearby towns, and was used in addition to alternative routes for the same journey over the course of a week. However, challenges for regular and sustained use of the Busway in relation to convenience were identified, corroborating previous qualitative analyses in the same cohort (Jones and Ogilvie, 2012). In our study, issues regarding security for bikes and the lack of provision of showers at workplaces were also recognised as barriers for physical activity on the Busway, alongside poor provision of lighting. These factors have been shown to discourage walking and cycling (Swiers et al., 2017; Félix et al., 2019). Prior analysis of this cohort also suggested the availability of workplace facilities contributed not only to increases in active commuting, but also to reductions in trips made by car (Patterson et al., 2020).

The Busway was used as a new location for walking and cycling for leisure, and provided access to greenspaces that were previously inaccessible, particularly for urban residents. The location of new infrastructure developments and their connection to other environmental factors are therefore important but may be experienced differently by different groups of people. Connecting rural communities to services such as employment centres and local shops may facilitate trip mode transition for groups previously dependent on car travel and allow for longer active journeys to be made. Conversely, urban dwellers typically had smaller activity spaces but new infrastructure allowed for new spaces such as greenspaces and nature reserves to be accessed. These findings align with those from studies that demonstrate the central role physical infrastructure can play in the uptake of walking and cycling amongst individuals who were previously inactive (Heinen et al., 2014; Panter et al., 2017).

4.2. Study contributions

Natural experimental studies can provide strong causal information in complex real-world situations (Ogilvie et al., 2020; de Vocht et al., 2021). In this study, we build on previously published work by exploring the spatial patterning of changes in activity using a combination of qualitative, quantitative and spatial data. Similar to a study reporting the results of free bus passes in London which drew on a range of data sources (Green et al., 2014), the methods applied in this study go beyond a typical evaluation by providing contextual information around intervention use. We quantify changes in the spatial patterning of physical activity using GPS data (*causal estimation*), and show, through the use of two detailed case studies, how this data can be enriched with qualitative interview data to explore underlying mechanisms (*causal explanation*).

Using individuals' geo-narratives provided an essential step in understanding mechanisms and sub-group effects in a local context. This holds particular importance for building healthy and equitable urban spaces. Insight can be gained into how groups with different travel needs, such as caregivers or people with disabilities, navigate new spaces. Understanding around modal shift and the uptake or displacement of behaviours for different groups can complement large administrative datasets which report the prevalence of commute and travel modes. As big data in the form of aggregated mobility information become increasingly available and help to provide population-level insights (Bort-Roig et al., 2014; Hu et al., 2021), researchers must also consider the value of integrating rich individual-level data. These may be collected by harnessing smartphone capabilities to record information contemporaneously through a single device while limiting participant burden (Rout et al., 2021).

Relying on a variety of evidence types in combination can ultimately help to gather a more detailed picture of behaviour change and inform interventions and policy decisions. As well as contributing to understanding of access needs surrounding structural interventions, evidence relating to the potential spatial displacement or uptake of new active travel may further inform planning relating to intersections and minimising conflict between travellers.

4.3. Study limitations

The study is not without limitations. The small sample size and the geographic specificity of the intervention meant that results may not be generalisable. As GPS data were collected over a period of 7 days, it was difficult to ascertain how routine the spatial behaviours observed were. However, self-reported use of the Busway and interview data was incorporated into research question 3 to provide a complementary information relating to habitual and infrequent Busway use over a longer period of time. Future studies may build on this by considering seasonal changes in mobility.

GPS data were not collected for all participants and so it is unclear whether the spatial patterns shown for physical activity are reflective of the broader sample. However, the available data allowed for key locations of physical activity to be visualised, both before and after the intervention, providing important baseline information. Using the data, it was also possible to develop, test, and refine a cleaning process to limit the effects of signal loss and stray, which may be replicated in future studies.

The methods reported in this study were retrofitted from the outset to fit existing data. For example, interview questions were designed without the intention of being integrated with spatial data and so it was not possible to perform a formal qualitative analysis. The value of this study, however, lies in exploring and demonstrating the potential of combining quantitative GPS data with qualitative information in the context of a natural experimental study design. The study is intended as an example to inform future study design and data collection, with a view to strengthening the evidence base for environmental interventions.

4.4. Conclusions and future directions for research

In recent decades, the use of GPS data and advanced GIS methods have emerged as viable options for enhancing understanding of associations between physical environments, behaviour and health outcomes. This study demonstrates the potential for triangulating GPS data with qualitative narrative information in a mixed methods evaluation of a natural experiment. In doing so, our study showed that use of the Cambridgeshire Guided Busway may contribute to long episodes of MVPA, and that how the Busway was used varied depending on residential location. For example, the transport infrastructure provided a new route for active commuting for rural residents, as well as access to greenspaces and a place for walking and cycling for leisure for participants living in more urban areas. Future studies may build on this example by carefully considering the strengths of a natural experimental study design and collecting high quality complementary information with which to identify mechanisms and develop stronger evidence on the pathways which act to influence use of spaces and changes in behaviour.

Funding acknowledgement

The Commuting and Health in Cambridge study was developed by David Ogilvie, Simon Griffin, Andy Jones and Roger Mackett. We thank all participants for providing data and all staff from the MRC Epidemiology Unit Functional Group Team, in particular for study coordination and data collection and data management.

The Commuting and Health in Cambridge study was initially funded under the auspices of the Centre for Diet and Activity Research (CEDAR), a UKCRC Public Health Research Centre of Excellence. Funding from the British Heart Foundation, Economic and Social Research Council, Medical Research Council, National Institute for Health Research and the Wellcome Trust, under the auspices of the UK Clinical Research Collaboration, is gratefully acknowledged. The study was later funded by the National Institute for Health Research Public Health Research programme (project number 09/3001/06). LS, TB, DO and JP are or were supported by the Medical Research Council [Unit Programme numbers MC_UU_12,015/6, MC_UU_00006/7]. The views and opinions expressed herein are those of the authors and do not necessarily reflect those of the NIHR PHR programme or the Department of Health.

Data access statement

The data cannot be made openly available because of ethical and legal considerations. Non-identifiable data can be made available to bona-fide researchers on submission of a reasonable request to datasharing@mrc-epid.cam.ac.uk. The principles and processes for accessing and sharing data are outlined in the MRC Epidemiology Unit Data Access & Data Sharing Policy.

Declaration of competing interest

The Commuting and Health in Cambridge study was developed by David Ogilvie, Simon Griffin, Andy Jones and Roger Mackett. Staff from the MRC Epidemiology Unit Functional Group Team were responsible for study coordination and data collection and data management.

The Commuting and Health in Cambridge study was initially funded under the auspices of the Centre for Diet and Activity Research (CEDAR), a UKCRC Public Health Research Centre of Excellence. Funding from the British Heart Foundation, Economic and Social Research Council, Medical Research Council, National Institute for Health Research and the Wellcome Trust, under the auspices of the UK Clinical Research Collaboration, is gratefully acknowledged. The study was later funded by the National Institute for Health Research Public Health Research programme (project number 09/3001/06). LS, TB, DO and JP are or were supported by the Medical Research Council [Unit Programme numbers MC_UU_12015/6, MC_UU_00006/7].

Appendix C. Supplementary data

The following is the Supplementary data to this article.

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Multimedia component 1.

Data availability

The authors do not have permission to share data.

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