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ARTICLE

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A mobile sense of place: exploring a novel mixed methods user-centred approach to capturing data on urban cycling infrastructure

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ABSTRACT
The paper explores a user-centred methodology for collecting, categorising, visualising, and interpreting data on urban cycling infrastructure and related cycling events. It develops a mobile mixed methods approach combining audio, video, sensor, and geospatial data sources. The method responds to stakeholders' feedback and related concerns about negotiating engineering, landscape and urban design, planning and policy elements in a way that addresses cyclists' needs. It is tested in a pilot study that combines infrastructure monitoring and perception data collection on eight newly built Major Cycle Routes in Christchurch, New Zealand. Data from one Major Cycle Route is used to explore methods of data categorisation, visualisation and interpretation. Based on the results of the pilot study, the paper discusses potential methodological changes or additions. It suggests future research opportunities and potential applications of the proposed methodology to support stakeholders' efforts to advance the planning, design and implementation of urban cycleways.

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1. Introduction

It is commonly accepted that the promotion of active transport in general and cycling in particular is an important aspect of sustainable transport planning. The multidimensional benefits of using bicycles instead of motorcars to move in and around cities are well known: Cycling does not produce greenhouse gases, noise or air pollution and it does not require any external energy source apart from the cyclists themselves. Next to walking it is therefore "the ultimate 'zero carbon' and environmentally friendly solution for personal transport" (Chapman 2007, 363). In contrast to motorised traffic, cycling has only minimal spatial requirements and it does not contribute to traffic congestion. It is an economically viable and affordable mode of transport. Due to low individual investments costs, it is one of "the most equitable of all transport modes" (Pucher and Buehler 2008, 496). In addition, regular cycling provides a variety of relevant health benefits including increased cardio-

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respiratory fitness. This reinforces “current efforts to promote cycling as an important contributor for better population health” (Oja et al. 2011, 496).

These benefits notwithstanding, many cities and towns still have low numbers of cyclists. The most frequently mentioned deterrent for potential cyclists is the real or perceived risk from motorists, particularly in the context of highly-frequented or high-speed traffic routes, even if these roads have dedicated cycleways and bike lanes (Lee and Moudon 2008; Winters et al. 2011). Cyclists also express safety and comfort concerns with regard to hilly environments and steep uphill or downhill grades (Grava 2003; Lee and Moudon 2008), badly maintained streets including rough surfaces (Lee and Moudon 2008), glass and debris on the street (Winters et al. 2011), and humps and kerbs (Joo and Oh 2013). Other frequently identified barriers to cycling are long distances and related travel times (Tilahun, Levinson, and Krizek 2007; Lee and Moudon 2008) and adverse weather conditions (Miranda-Moreno and Nosal 2011; Nankervis 1999), particularly ice and snow (Winters et al. 2011).

Continuous bike lanes (Lee and Moudon 2008), separated from the main traffic, noise and pollution (Winters et al. 2011), close to people’s homes and leading to desired destinations (Hull and O’Holleran 2014) have been considered to encourage cycling. The quality of the environment along the route with regard to visual interest (Fleming 2012) and scenic beauty (Winters et al. 2011) are additional motivators that have influenced cycling behaviour. A city that can provide a safe, well-designed, and well-maintained bicycle infrastructure network, including physical separation from high volume traffic, and preferably scenic routes with less noise and pollution in a favourable landscape setting, should be able to attract more cyclists. This has been confirmed in a number of recent studies (Buehler and Dill 2016; Heinen, Maat, and Van Wee. 2011; Oliva, Galilea, and Hurtubia 2018; Hull and O’Holleran 2014). In addition, if climatic conditions are less harsh, the topography relatively flat, and the urban form fairly permeable to allow cyclists to choose shorter routes (Oliva, Galilea, and Hurtubia 2018), a city should be well positioned to make cycling more popular and increase the share of active modes of urban transport.

Urban authorities may, however, face criticism from sectors of the public when budgets are diverted to cycling infrastructure or when that infrastructure affects them adversely. The term “bikelash” describes the “perceived wave of ‘angry’ community opposition to new cycling infrastructure” (Wild et al. 2018, 505). Such opposition comes mainly from retailers, conservative voters and residents, but also – perhaps surprisingly – from cyclists who feel that they have not been properly consulted. In order to address the bikelash phenomenon, bottom-up community engagement and “ongoing consultation with cyclists that treats them as key sources of technical expertise on the design and implementation of cycle lane projects” (Wild et al. 2018, 515) have been suggested.

Cycling has been understood as “a mobile engagement with landscape mediated by bicycle” (Cook and Edensor 2017, 2) including “fleeting, ephemeral and often embodied and sensory aspects of movement” (Spinney 2011, 162), visual and non-visual experiences (e.g. auditory, olfactory, and tactile sensory perceptions) as much as encounters with historical and cultural dimensions (Van Dyke 2013). Compared to car drivers, cyclists are exposed to a more direct, richer and “broader sensory landscape” (Jungnickel and Aldred 2014, 246). Cycling is not about the distant observation of landscapes that fly past. It is a continuous and active bodily experience within evolving landscapes where cyclists need to pay “particular attention to road surfaces and obstacles that would be irrelevant for car drivers" (Cook and Edensor 2017, 2). However, experiential-qualitative aspects of mobility have often been ignored in the travel and transport literature (Cresswell 2006). In this paper, we explore ways of capturing data on such experiences. The purpose of our research is to develop and explore a novel method for data collection and interpretation that may help increase our knowledge about how cyclists perceive urban cycling infrastructure. This is relevant for planning and design decisions as much as for the improvement of existing cycling infrastructure.

2. Methodology

The aim of this paper is to develop a user-centred methodology to simultaneously gather different types of data *in situ*, and to explore methods of data visualisation and interpretation. We developed the methodological approach in response to stakeholders' feedback and related concerns about negotiating engineering, landscape and urban design, planning and policy elements in a way that addressed cyclists' needs. The paper explores a mobile method that combines audio and video data and sensor-based quantitative metrics. The data was generated by a cyclist while cycling (user-generated data); however, the data is not about the cyclist, but about the cycleway and its perception. We refer to mobile methods in a two-fold way: First, with regard to the so-called "mobilities turn", a broader paradigm in the social sciences focusing on people on the move and using empirical (ethnographic) research methods (Büscher and Urry 2009; Büscher, Urry, and Witchger 2011). Second, with regard to the use of mobile technologies and devices for research purposes and related forms of data collection (Boase and Humphreys 2018).

The method was tested in a pilot study where we collected data on eight newly built Major Cycle Routes in Christchurch, New Zealand. In this paper, we use data from one exemplary case, the Papanui Parallel Major Cycle Route, to discuss methods of data categorisation, visualisation and interpretation. We chose this particular case, as it allows us to discuss a range of cycling events in relation to existing bicycle infrastructure. Our study does not analyse or evaluate existing cycle infrastructure *per se*. However, it is hoped that the proposed methodology encourages new ways of carrying out cycleway analysis and evaluation to help improve existing and future cycleways, and to foster the production of transferable knowledge in New Zealand and elsewhere.

2.1. Research setting and context

Christchurch – our research setting – is the largest city of the South Island in New Zealand. It is predominantly topographically flat, with a relatively dry and temperate climate, and a historically routed cycling tradition (Bui 2015) which makes it potentially suitable for a larger-scale uptake of cycling. Following an extended earthquake sequence that began in 2010 and resulted in the demolition of over 70% of the inner city, the city's future was reconsidered in light of major planning and policy decisions. Following widespread public consultation under the award-winning *Share an Idea* campaign, and in light of the above listed benefits associated with investment in urban cycling infrastructure, the Christchurch City Council (CCC) set out a long-term vision and committed to building 13 Major Cycle Routes (MCR) across the city (CCC 2018a, 2018c)(Figure 1). Funding was subsequently approved in 2014 with an original investment of NZ$156 million. This

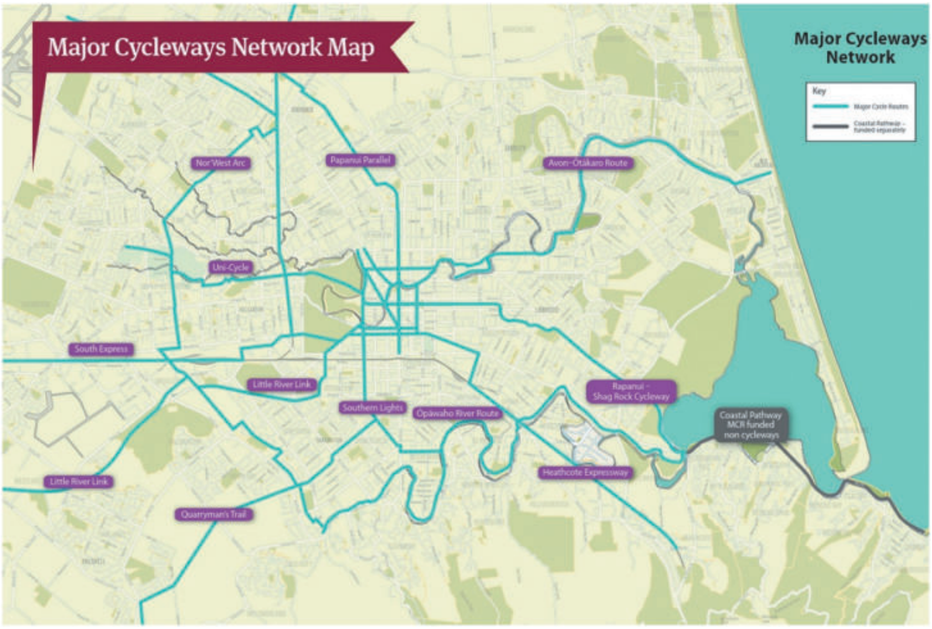


Figure 1. Image of planned Major Cycleways network as proposed by stakeholders. Source: Christchurch City Council (CCC), https://www.ccc.govt.nz/assets/Images/Transport/Cycling/Network-map.png.

investment was increased to approximately NZ$252 million in 2018. A large part of the funding came from the New Zealand Transport Agency (NZTA) via their Urban Cycleways Programme (Law 2018). The anticipated completion date of the last MCR is 2028 (CCC 2018d). The intention is that MCRs connect "suburbs, shopping areas, businesses and schools" (CCC 2018e) and attract both recreational and non-recreational cyclists.

The MCRs are expected to deliver a total of NZ$1.2 billion of tangible health, environment, decongestion and safety-related benefits over a period of 40 years (Cairns 2015). The projects are highly relevant for a city where the automobile is the dominant mode of urban transport. Based on the 2013 census, 84% of the population in Christchurch travels to work by car (Statistics New Zealand 2015a, 21), an increase of 1.7% compared to 2006. This is a highly unbalanced modal share, even for New Zealand standards, where car ownership rates are very high and the use of public transport is generally low. In comparison, in New Zealand's capital Wellington (comparable to Christchurch in terms of population size and regional importance), 64.6% of the population uses the car to get to work (Statistics New Zealand 2015b, 10). Notably, even Greater Auckland, New Zealand's most populous sprawling metropolitan region, has fewer car commuters than Christchurch (Statistics New Zealand 2014). However, commuter numbers show a different trend with regard to cycling. Seven percent of Christchurch's population travels to work by bicycle, a number that has slightly increased since 2006 (Statistics New Zealand 2015a, 27) and is higher than in Wellington and Auckland.

At the time of our study, eight of 13 MCRs had been partially or fully implemented (CCC 2018e). Counting sensors installed on some routes indicate that the new infrastructure is well used and that cyclist numbers have increased (CCC 2018b). Thus, the investment in cycling infrastructure has the potential to encourage *systemic* and *enduring* change for urban transport and the urban system in general. However, such change rarely occurs without conflicts and setbacks. The implementation of MCRs has resulted in negative feedback from some local residents and businesses who primarily criticised the loss of on-street car parking spaces in front of their houses or businesses (Northcott 2017; Law 2016; Truebridge 2017). Another proposal where existing on-street car parking was retained but where two cul-de-sacs were connected and existing houses demolished was also highly controversial (Mitchell 2016). While such reactions could be downplayed as typical bikelash phenomena, they show that the new bicycle infrastructure does not necessarily meet the needs of everyone, particularly those who perceive they are dependent on travel by car. This is particularly challenging in a sprawling, low-density city like Christchurch that has been designed for and around the motorcar since World War II. The conflicts reveal a discrepancy between existing transport patterns (although known to be unsustainable) and alternative concepts informed by sustainable urban design and planning strategies.

Some cyclists have expressed concerns about the utility and safety of some new cycle lanes, though much of this relates to the inner-city network that is not technically part of the suburban MCRs. Nonetheless, high-profile accidents (Young 2017) may have clouded perceptions of the MCRs and reduced uptake among the "interested but concerned" (Portland Bureau of Transportation 2020). In this context, it seems timely to explore ways of capturing users' perceptions in combination with infrastructural metrics.

2.2. Stakeholder involvement

Our research methodology included a stakeholder involvement phase with relevant staff at CCC and the Greater Christchurch Partnership (GCP) between August and October 2017, followed by two presentations (October 2017 and May 2018) that provided an update on the research process and an opportunity to give feedback. Both organisations are key players in urban development, planning and urban transport strategies in Christchurch. The main goals were to collect relevant information about the MCRs, and to identify potential research areas and related research questions.

Qualitative interviews ($n = 8$) were conducted with CCC and GCP staff across different departments including a councillor (CCC), a MCR project manager (CCC), an urban designer (CCC), a traffic engineer (CCC), a transport planner (CCC), a landscape architect (CCC), a resilience officer (CCC), and a travel management project leader (GCP). Interviews were transcribed, and a qualitative content analysis was carried out. A review of relevant policy documents and funding assessment reports was conducted. The review of stakeholders' accounts and relevant documents identified potential focal areas for research. One key finding was that MCR users' experiences were difficult to capture and to include in decision-making processes. Our findings were presented to the stakeholders in October 2017. Feedback was sought, particularly to confirm a potential research area. In response to the feedback and taking into account an internal feasibility study of timeframes and available resources, it was decided to proceed with one key research question: *How do users experience the MCRs?* The research rationale was based on the assumption that positive cycling experiences influence people's choice to use their bikes more often and use more active travel modes for future trips (De Vos et al. 2019). Focussing on actual user experiences was considered as a counterbalance to "conventional" rationales, e.g. those that focus on economic benefits.

2.3. Method

Based on the outcomes of the stakeholder involvement process, we developed a mobile method that combines user-generated video and audio data, sensor-based monitoring of cycling infrastructure, and geospatial mapping (Table 1a) to explore the relationship between the physical environment and cyclists' perceptions of satisfaction and comfort. The sensor and geospatial data (accelerometer, gyroscope, speed, and GPS) was collected with a smartphone attached to the bike. Video and audio data was recorded together with the sensor data using the same mobile device attached to the bike (for technical details refer to the "pilot study results" section). We used a 360 degree camera, attached to the mobile phone, to provide data for a comprehensive video analysis of the surrounding landscape and the cyclist's bodily reactions.

Our method builds upon the *parcours commentés* qualitative method (Thibaud 2001), also known as "commented walks" (Thibaud 2013). Thibaud's method captures verbalised *in situ* experiences of study participants while walking on an agreed route. It has been applied in previous studies, e.g. in urban ambiances (Said 2013) and transportation research (Meissonnier and Dejoux 2016). Thibaud's method and other walking interview techniques such as the "go-along" method (Kusenbach 2003; Carpiano 2008), require participants to be accompanied by a researcher to encourage a continuous verbal flow of information. However, as talking to participants while cycling is often not a feasible option, we adapted Thibaud's *parcours commentés* method, and collected recorded video and audio data from cyclists via smartphone applications. This method, which we call "commented cycling", allows participants to freely talk about their perceptions and experiences – what they see, hear, smell or feel – while cycling unaccompanied on an agreed route. The cyclist's verbal comments are captured as an audio recording.

In Thibaud's method, the researcher follows up each trip by semi-structured interviews to allow participants to "go over what had just been experienced" and to use the short-term memory "to reinterpret and round out the initial comments" (Thibaud 2013, 30). Similarly, following the ride, our participants were invited to reflect on their perceptions. The combined video and audio data was shown to them and they were asked to assess

Table 1. (a). Overview of collected data, (b). Example of combined data of a cycling event.

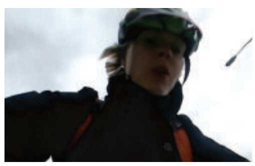
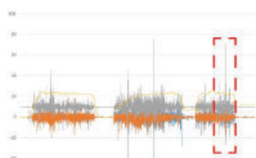
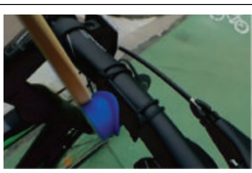
Data category	Data type(s)	*Collection time*/Method or device used for data collection
Sensor data	Accelerometer data (acceleration) Gyroscope data (angular velocity) Speed	*While cycling*/Samsung Galaxy S7 Edge smartphone
Video data	360 degree video recording (spatial and environmental context and cyclist)	*Whicle cycling*/Giroptic iO Spherical Video Camera
Audio data	Cyclist's recorded verbal comments (perception data)	*While cycling*/Giroptic iO Spherical Video Camera
Geospatial data	GPS (location)	*While cycling*/Samsung Galaxy S7 Edge smartphone
Rated cycling events	Reflective Likert-scale rating of experienced cycling events (1–5; from very positive to very negative)	*After cycling*/interview with cyclist; review of video and audio data

the quality of commented experiences on a five-point Likert scale from 1 being very negative, to 5 being very positive. For example, if cyclists experienced safety issues related to motorised traffic, the audio and video helped them recapture the situation and make a judgement, e.g. "This was a near miss; a very negative experience".

Table 1b shows an example of different types of data that have been combined to illustrate a particular cycling event (a strong unexpected hidden bump on a green painted area of the cycleway that caught the cyclist by surprise).

Several studies (Borgman 2003; Bíl, Andrášik, and Jan 2015; Calvey et al. 2015; Joo and Oh 2013; Feizi et al. 2019) use instrumented bicycles equipped with sensor technology to measure the condition of cycle infrastructure (e.g. transmitted road vibrations, noise levels, surface conditions, journey interruptions). Other studies focus on cyclists' perceptions and experiences (Fernández-Heredia, Monzón, and Sergio 2014; Snizek, Sick Nielsen, and Skov-Petersen 2013; Li et al. 2012). A few studies combine sensor-based infrastructure assessment with cyclists' perceptions including Borgman's (2003) pioneering Dutch study, Calvey et al. (2015) "IntelliBike" research, and more recently Gao et al. (2018) cycling comfort evaluation in China. These studies have in common that they use questionnaire-

Table 1b.. Example of combined data of a cycling event

<table>
<tr><td colspan="3">Event: Sharp unexpected bump, not visible in green surfacing)
Category: SRFQ
Video time: 6:57
Rated: 5 (very negative)</td></tr>
<tr><th>Spatial situation (video data)</th><th>Cyclist's reaction (video and audio data)</th><th>Sensor data</th></tr>
<tr><td>
Front view – the green surface seems smooth; no visible bumps or holes</td><td>
Spontaneous expression of surprise: 'Oof!' after an unexpected sharp bump; looking down - what happened?</td><td>
The accelerometer data shows a significant peak (ca. 70 m/s2)</td></tr>
<tr><td rowspan="2">
Downwards view – no visible bumps or holes</td><td>Cyclist's comment shortly after event:

'Ok – there was a very surprising bump on the cycleway that wasn't really easy to see because it was in the green area.'</td><td rowspan="2">
The GPS data informs geospatial mapping showing where event occurs</td></tr>
<tr><td>Reflective Likert-scale rating of event (post-cycling):

5 (very negative)</td></tr>
<tr><td colspan="3">Data sources (including images): The authors, 2018. Map layer: Google Maps (Map imagery and data ©2020 Google)</td></tr>
</table>

based surveys to assess cyclists' perceptions. Our mobile method makes two fundamental changes to the above-mentioned research designs.

First, our method uses compact and affordable mobile technology instead of separate sensors, instruments and devices installed on instrumented bikes. Regular off-the-shelf smartphones are equipped with sensors to capture accelerometer, gyroscope, noise, light, temperature, and GPS data. This is appropriate as although smartphones have not previously been used to assess bicycle infrastructure, they have been used in automobile-based studies to monitor the quality of roads (Badurowicz, Cieplak, and Montusiewicz 2016; Badurowicz and Montusiewicz 2015; Allaire and Hanson 2017). Our approach is not dismissive of studies that use instrumented bicycles as we recognise that the use of inexpensive mobile phone technology does not replace the need for precise instruments such as calibrated transducers, particularly for purposes that require high accuracies of measurement. What we suggest, however, is that there are some advantages in using an easy-to-use mobile method that reduces the costs of instrumentation and allows even unexperienced users to carry out basic sensor-based measurements of bicycle infrastructure.

The second difference between our method and methods used in existing research is that our method captures cyclists' perceptions directly and immediately *in situ* in a way that can be synchronised with the sensor-based data. Previous studies found that video, and particularly a combination of video and audio, are powerful tools in mobile ethnographic cycling research (Spinney 2011; Lloyd 2019). This is an essential methodological difference to questionnaire-based surveys that collect perception data detached from the immediate experience. It also differs from traditional "go-along" interviews, as participants might be tempted to stop commenting without getting prompts of an accompanying researcher. However, this may also be an advantage as participants are not influenced, distracted or interrupted by an interviewer.

Information produced with this method could potentially be used to improve levels of service (e.g. bicycle infrastructure maintenance and safety) and inform future urban planning and design decisions (e.g. through the reconsideration of existing routes or design details, or integrating landscape features). Our approach does not produce contextually "thick" narrative accounts like those created with the help of in-depth qualitative interviews. Instead, it encourages fast, quantified, and short reflective statements by cyclists using the cycle routes. Potential advantages and disadvantages of this approach are discussed in the discussion section.

3. Pilot study results

The proposed method was tested in a pilot study between January and May 2018. The chosen test sites were eight newly built MCR sections in Christchurch that had been fully or partly implemented at the time the pilot study was carried out (refer to Figure 1 for map of routes): Northern Line (included but not named in Figure 1; runs between Papanui Parallel and Nor'West Arc), Papanui Parallel, Rapanui-Shag Rock Cycleway, Coastal Pathway, Tennyson Street (implemented part of Southern Lights), Little River Link, Ilam (already implemented part of the Nor'West Arc) and Uni-Cycle. The study included three distinctive stages. First, *in situ* testing of gear and software (January – February 2018).

Figure 2. Bike used in the pilot study. (Photo: The authors, 2018).

Second, data collection on the eight MCRs (March 2018). Third, categorisation, visualisation and interpretation of data collected on the Papanui Parallel MCR (April – May 2018).

3.1. Equipment

The most important equipment item was a regular, inexpensive city bike (Giant; Figure 2). This bike was chosen as it was thought that in order to measure the full impact of cycleway surface roughness, it was best to use a bike without a suspension system. The selected mobile device was a Samsung Galaxy S7 Edge smartphone with 32GB internal memory running on the Android operating system. The Edge model was chosen due to a slightly better battery performance when compared to the standard model. The device featured built-in sensors needed for the study: accelerometer, gyroscope, speed, and global positioning (GPS). In the pilot study, light and sound data were recorded and saved. These may be relevant for specific environmental analysis, for example relating measured noise levels to cyclists' sensory experiences, however we did not use this data due to time constraints at the data analysis stage. The phone was attached to the handlebar with the help of a Quad Lock Bike Kit for Samsung Galaxy S7 (Figure 3). A 360-degree camera was chosen to record audio and visual content.

In contrast to regular cameras such as a built-in smartphone camera, the 360-degree camera covered the entire field of view (front, sides, back, top, down) of the moving bicycle. This allowed for more detailed image analysis of the environmental context and the cyclist's actions and expressions in relation to the audio and sensor data. The chosen camera model (Giroptic iO Spherical Video Camera for Android devices) was directly attached to the smartphone (Figure 3). This avoided cluttering the handlebar with devices. The phone had to be positioned upside down in order to attach the 360 degree

Figure 3. Smartphone with attached Giroptic iO 360-degree camera. (Photo: The authors, 2018).

camera in an upright position. This had no effect on the data collection. The total investment for the equipment (bike, smartphone, Quad Lock and camera) was less than NZ$ 2,000 (ca. US$ 1,350).

Prior to our data collection, we tested the equipment extensively in the field. There were no problems with the operation of the bicycle or mobile device. However, we experienced some problems with the Giroptic iO 360-degree camera. This ranged from software-related communication issues between phone and camera (e.g. recording and data storing issues), frozen frames, limited battery life of the camera, and a weak physical connection between phone and camera. The camera lost connection while riding on uneven surfaces and fell off once. However, we were able to implement pragmatic solutions to these technical challenges. We also tested the camera's sound capturing capabilities at different weather and noise level conditions. The cyclist's comments and descriptions remained comprehensible and an external microphone was not needed.

3.2. Mobile apps

There are many apps designed to read, display and export Android sensor data on mobile devices. The Samsung Galaxy S7 Edge sensors include acceleration, linear acceleration, Gyroscope data, GPS data, speed, light and sound levels, magnetic field, device orientation, and pressure (barometer). We were particularly interested in accelerometer and gyroscope data, which is used (in combination with speed data) to measure the impact of surface conditions on the bike (e.g. rough surfaces or bumps). Accelerometer data depicts the acceleration (direct movement) of the bike along the three axes (x, y, z). Gyroscope data captures "the angular speed of an object and the axis about which the object is rotating [the tilt angles of the bike while it is moving] within a specified time interval" (Joo and Oh 2013, 3). Rotation about the x-axis has been referred to as "roll" (leaning towards the left or right); about the y-axis as "pitch" (e.g. front heel going up when moving across an obstacle); and about the (vertical) z-axis as "yaw" (moving left or right, usually by turning the handle bar to the left or right) .[1] GPS data was recorded for the geospatial mapping.

We tested 12 different apps. All apps were acquired on Google Play. Some of them were free while others were purchased. The apps were first tested on a short route (part of the Papanui Parallel MCR) for user-friendliness, data collection and recording options, compatibility with the camera and battery use. The route included different road surfaces and took about one minute to ride at moderate speed. Parallel use of the sensor apps and the camera app was tested to determine if the sensor apps were able to run in the background. The phone's battery life was not greatly affected by any of the sensor apps.

A second test was conducted on a longer test route of approximately eight minutes to test the long-term functionality of different apps. A pre-selection of suitable, "favourable" apps (apps that recorded desired sensor data reliably and exported it in an uncomplicated and timesaving way) was carried out. In a third test, favourable apps were run parallel while steering around obstacles. The data obtained was analysed in Microsoft Excel to identify possible measurement inaccuracies. Different default settings resulted in different sampling results. Therefore, app settings had to be brought into line for consecutive tests. Some apps could not be compared as they were not able to record simultaneously in the background.

Based on the tests, the free AndroSensor app (developed by "Fiv Asim"; not to be confused with Andro Sensor by "Snipe Studio") turned out to be the most suitable app for the study. This was because it ran smoothly in the background and in combination with the camera app, collected reliable sensor data, and exported multiple sensor data as one comprehensive and detailed Microsoft Excel file (CSV format), which could be visualised. Default settings could be changed upfront with regard to sampling intervals or units. The other tested apps showed at least one but often several deficiencies that made them less suitable.

Figure 4a. Drainage kerb. (Photo: The authors, 2018).

Figure 4b. Speedbump. (Photo: The authors, 2018).

3.3. Test runs

We wanted to test if we could recognise distinct "patterns" that resulted from particular obstacles such as kerbs or speed bumps when visualising accelerometer and gyroscope data in a graph. The tests were conducted at different sampling frequencies (measured in Hertz (Hz) where 1 Hz corresponds to one measured sample per second) of accelerometer and gyroscope data. This was done as different sample frequencies can lead to different results.

First, we tested the same app on the same route at different sampling frequencies. The AndroSensor app was used with several runs for each sampling frequency, starting at 20 Hz and going up to 60 Hz in steps of 10. Results showed that at 20 Hz the extreme accelerometer data peaks at bumps varied greatly with up to 35 m/s^2 difference per bump. Even at 60 Hz there were still differences. We concluded that these variations could a

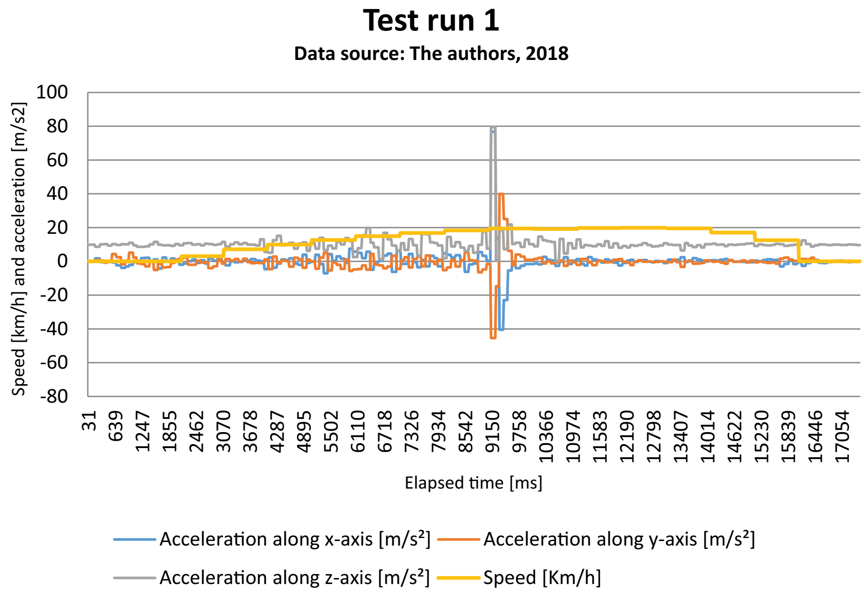


Figure 5a. First drainage kerb test run (accelerometer and speed sensor data at 60 Hz sampling frequency).

b

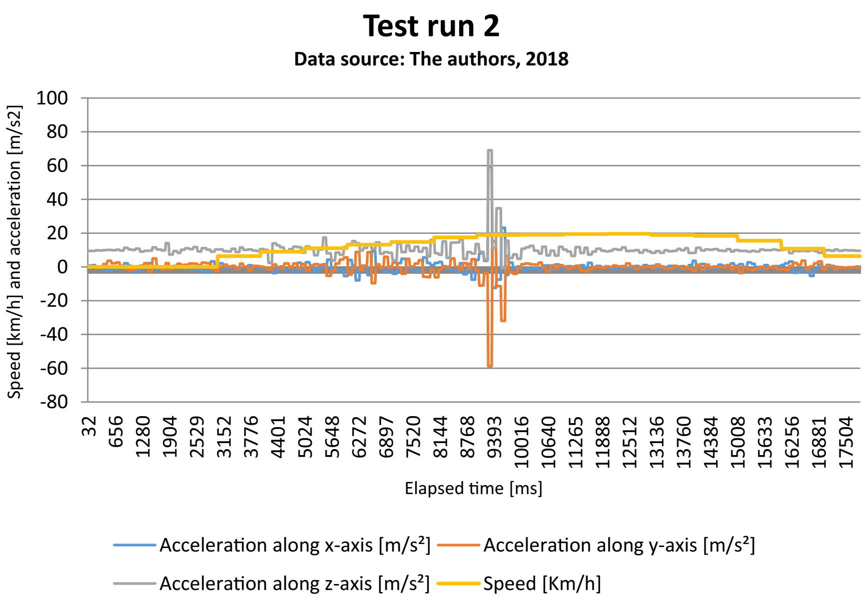


Figure 5b. Second drainage kerb test run (accelerometer and speed sensor data at 60 Hz sampling frequency).

not be avoided unless testing was done under laboratory conditions. Overall, a higher sampling frequency (60 Hz) led to similar results between test runs. The gyroscope data showed similar patterns as the accelerometer data, already at lower frequencies.

Then, with 60 Hz as the pre-set sampling frequency, two types of obstacles on an otherwise flat section were tested repeatedly with the AndroSensor app. The different test runs were compared. The first obstacle, a drainage kerb running across the cycleway (Figure 4a), was visible in the form of peak levels in the accelerometer data graph and created similar patterns in both runs (Figures 5a and 5b). The second obstacle, a speed bump at a pedestrian crossing (Figure 4b), showed a change in the accelerometer values but was not similar for both runs.

Some obstacles created similar patterns recognisable in accelerometer sensor data visualisations. Other obstacles didn't seem to produce clearly recognisable patterns, even at higher sampling frequencies. We concluded that accelerometer sensor data visualisations might have differed, for example, due to speed or the general style of biking. However, while we conducted multiple test runs that produced similar looking graphs,

Table 2. Preliminary inductive category system based on 30 Likert-scale-rated cycling events on the Papanui Parallel MCR (first 7.5 minutes).

Inductive category	Cycling event (rating); video time
Bike Infrastructure (BINF)	Between cars and shop front (3 neutral); 0:56
	Lane narrows to 2-way lane (4 negative); 1:33
	Narrow 2-ways shared path in front of shops around poles (4 negative); 3:12
	Enter quiet shared street. Narrow. Tight turn (4 negative); 3:30
	Speedbump (3 neutral); 3.50
	Speedbump, slows cars down (2 positive); 4:08
	Speedbump bypass (1 very positive); 4:20
	Narrow between 2 parked and 1 oncoming car (4 negative); 4:23
	Pedestrian refuge crossing point (3 neutral); 4:46
	Wide lane (2-way, no centre line) (2 positive); 4:54
	Enter narrow 2-ways shared footpath (4 negative); 5:20
	Dangerous driveway right on to cycle lane with no visibility (5 very negative); 5:25
	Parked cars close. Doors open into cycle lane (4 negative); 6:13
Interactions between cyclist and other users (humans; animals; vehicles) (INTR)	Stopped car turning left across lane waits (3 neutral); 0:50
	Pedestrians cross without looking (4 negative); 2:00
	Pass cyclist from other direction (3 neutral); 2:02
	Jogger crosses lane (3 neutral); 5:00
	People crossing (3 neutral); 6:35
Traffic signals and signs (SIGN)	Bad traffic lights – almost hit by car (5 very negative); 0:00
	Bicycle traffic lights (42 sec stop) (3 neutral); 2:22
	Lights (24 sec.) Unable to manually trigger lights (4 negative); 5:30
	Short wait for lights to change (2 positive); 5:54
Surface quality (SRFQ)	Smooth surface (2 positive); 0:35
	Bump over kerbing (4 negative); 6:43
	Sharp unexpected bump, not visible in green surfacing (5 very negative); 6:57
Environmental quality (ENVR)	Noisy. Busy traffic (4 negative); 7:35
Debris and obstacles (DEBR)	Wheelie bin in lane (3 neutral); 6:35
Wayfinding (WAYF)	Clear on-road signage indicating 2-way-lane (2 positive); 1:41
	Direction of path unclear (4 negative); 3:20
	2-ways separated lane begins. On-road indication clear from distance (2 positive); 4:40

Data source: The authors, 2018

the visual comparison was not sufficient to draw definite conclusions. Additional data analysis would be needed to make a more robust interpretation of obstacle patterns. However, for the purpose of this study, it was sufficient to simply identify bumps in the road. We used a 60 Hz sampling frequency for further data collection.

By default, the AndroSensor app captured accelerometer data as vector-based data for the x, y, and z axes related to the device's position (device coordinates). Changing the device's position, e.g. from flat to upright, will therefore influence accelerometer values along different axes. The app allows changes to be made to global coordinates. Using the global coordinate system, axes always point in the same direction regardless of the devices' position[2] and it has been suggested to that it is best to apply global coordinates when recording accelerometer data (Badurowicz and Montusiewicz 2015). Our test runs confirmed that using global coordinates, the phone's orientation did not affect the data output with regard to the different axes. However, the phone's orientation had an impact on the level of vibration being recorded. The stability of the device and its oscillation were also affected by its position. In our tests, in the vertical position, bumps were clearly detected with z-axis accelerometer values of 70 to 90 m/s^2. In the horizontal (flat) position, peak values reached 40 to 70 m/s^2, and in the diagonal position only 20 to 30 m/s^2. As a consequence, the phone was subsequently mounted in an upright (vertical) position.

GPS data was recorded with the AndroSensor app and used to calculate speed. The GPS data was checked against the actual route on Google Maps and confirmed to be relatively precise. However, the camera did not export GPS data, and it became a challenge to match and interpolate GPS points with video and audio data to get

Figure 6. Visualisation of GPS data in combination with accelerometer, speed, and categorised and rated cycling events on a Google map.

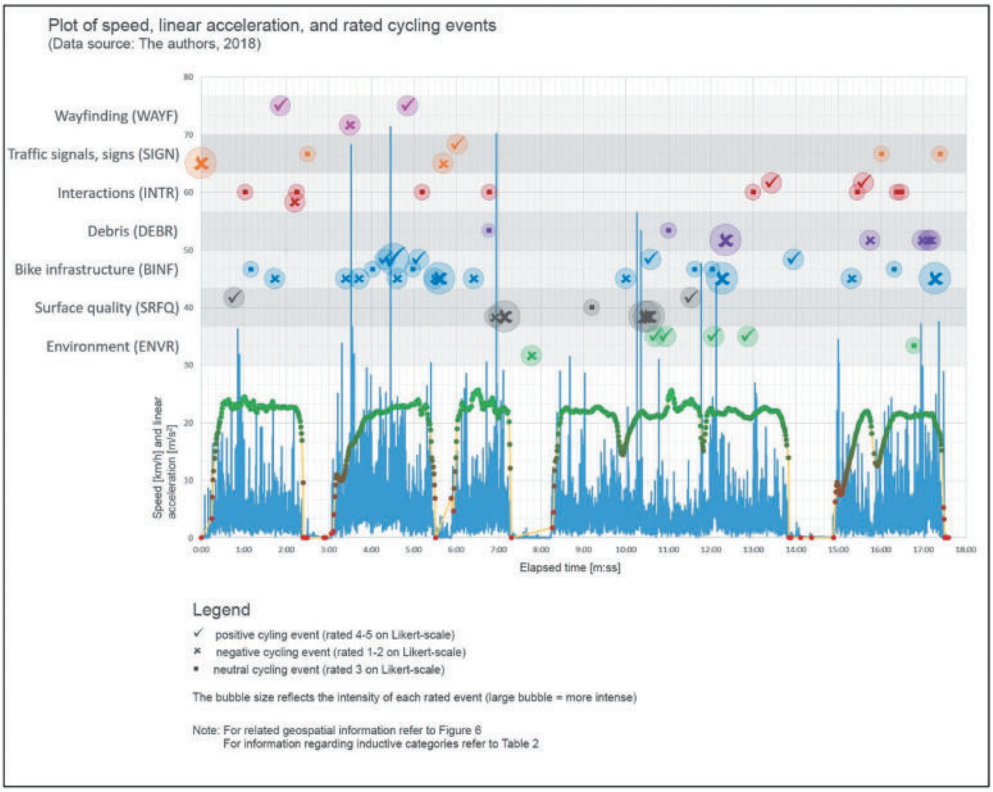


Figure 7. Visualisation of simplified accelerometer data, speed, travel time, and categorised and rated cycling events.

exact overlays. The only data that allowed for exact overlays were the time stamps of both AndroSensor and camera. To align the different starting times of AndroSensor and the video and audio recording, we manually synchroned both data sets through a "start slap" on the phone. This strong tap on the smartphone was visible on the video, audible in the audio recording, and showed as a varying value in the accelerometer data. Based on this signal, the time difference between sensor and video and audio data was adjusted to create a common time stamp for both data sets.

3.4. Data collection, rating and categorisation

After the testing phase, data collection on all eight MCR was carried out in March 2018 by a test cyclist. Two data sets were collected simultaneously for each journey. First, using our "commented cycling" method, the test cyclist continuously commented on her experiences while cycling. Her comments were recorded as combined video and audio files during the entire trip. Second, the AndroSensor App was used with a 60 Hz sampling frequency to record sensor data (accelerometer, gyroscope, speed, and GPS). While cycling and commenting, the test cyclist supervised the correct functioning of the AndroSensor and 360-degree camera apps to ensure the correct recording of all data.

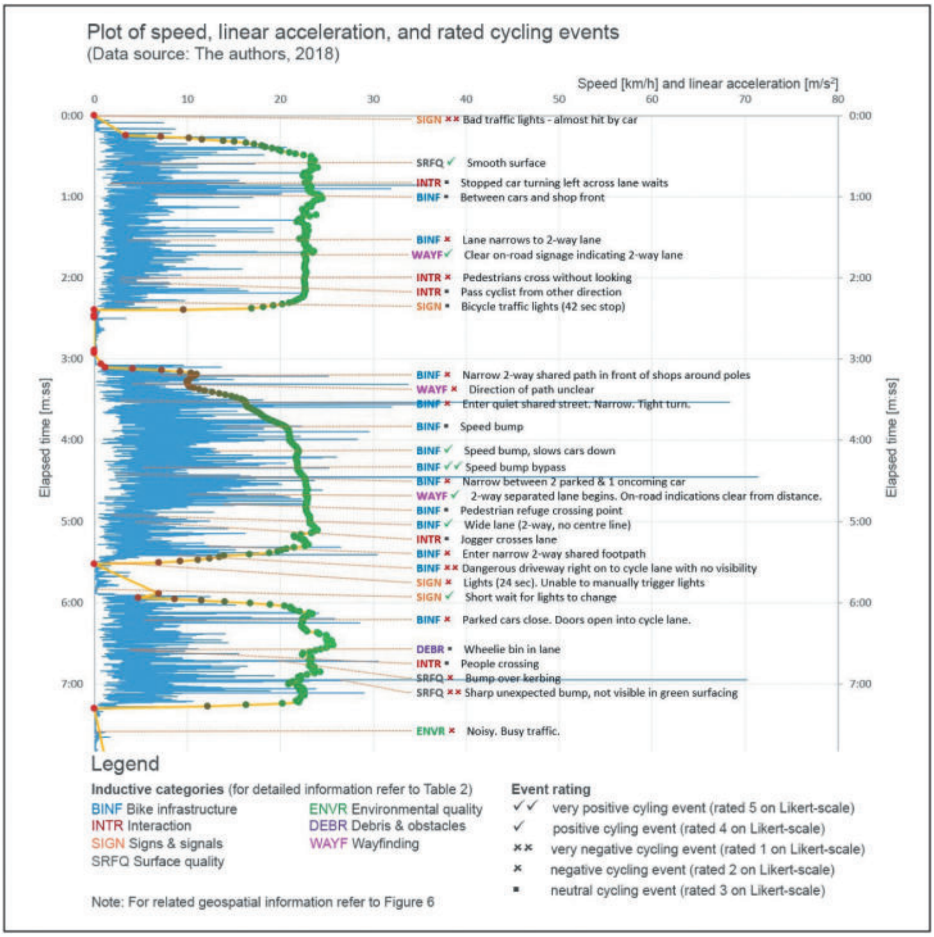


Figure 8. Visualisation of accelerometer data, speed, travel time in combination with categorised and rated (clustered) representations of cycling events.

After each trip, the data was saved. The video files tended to be very large and had to be regularly downloaded to allow for further recordings. This required a systematic process of storing and organising the large data sets. In order to keep the data manageable, longer trips were broken up into shorter sections (ca. 15 minutes). The sensor data was exported as a Windows Excel spreadsheet. After each ride, the test cyclist examined the video and audio data and identified and assessed the quality of distinctive cycling experiences (which we called "cycling events") on a five-point Likert scale (where 1 = very positive and 5 = very negative).

Data categorisation involved the following steps: The events were transcribed from the audio data with exact video times (format hh:mm:ss) and listed in a spreadsheet together with their Likert value. The events were then coded/categorised following an inductive qualitative content analysis approach (Zhang and Wildemuth 2017). Accordingly, the resulting categories were not based on a pre-determined framework but evolved throughout the categorisation process. Table 2 shows a preliminary category system based on 30 identified and rated cycling events on the Papanui Parallel MCR. Finally, events were combined with the sensor data in an Excel spreadsheet (including their Likert value and main category). The video times and sensor data times were manually synchronised via the "start slap" method resulting in one combined time stamp for both sets of data.

3.5. Data visualisation

We explored different ways of visualising combined data by using the preliminary category system based on data collected on the Papanui Parallel MCR (Table 2). The first two visualisation examples (Figures 6 and 7) depict roughly the first 7.5 minutes of the trip. The final example (Figure 8) shows the entire trip (ca. 17.5 minutes).

Figure 6 depicts a spatial representation of the GPS route data on a Google map in combination with accelerometer data, speed and categorised and rated cycling events (Table 2). The speed line (green/orange/red) follows the GPS route on the map. The green line symbolises speed greater than 10 km/h; the orange-red line symbolises slow speed (<10 km/h) or stops. Accelerometer data peaks that indicate rough surfaces, bumps or other obstacles are shown as grey circles along the route. The bigger the circle the higher the accelerometer data peaks. Categorised and rated cycling events are depicted next to the route in their distinctive category colour (Table 2). The Likert-scale rating of each comment has been symbolised: Two ticks = very positive (5 on the Likert scale); one tick = positive; (4 on the Likert scale); a small black box = neutral (3 on the Likert scale), a red cross = negative (2 on the Likert scale), and two red crosses = very negative (1 on the Likert scale).

Figure 9. Bumpy design detail. Drainage kerb cuts through cycleway to connect disjointed street gutters. (Photo: The authors, 2018).

While this representation communicates spatial information and helps identify critical points of both sensor and perception data on the map, it does not provide detailed sensor data information or a structured overview of categorised and rated cycling events. It also does not include information about the travel time.

The second visualisation example (Figure 7) combines detailed information on surface roughness (simplified accelerometer data; values on x-axis), speed (orange/green line; values on x-axis), travel time (y-axis), and categorised and rated cycling events. Compared to the first visualisation, the detail of sensor information has increased. However, perception data is still represented in an unstructured format.

The final example (Figure 8) depicts the same detailed sensor-based information on surface roughness (y-axis), speed (y-axis) and travel time (x-axis). In addition, it features a categorised and rated representation of perception data. While more detailed text-based information has been removed from the chart, different categories are now clearly shown. Different colours for each category (see Table 2) support this structured approach. Likert-scale-based rating information has been simplified: Tick (4–5), box (3), cross (1–2). However, the different bubble sizes reflect the intensity of each rated event. For example, the large purple bubble with a cross at about 12.5 minutes travel time depicts a very negative experience, obviously related to debris or obstacles on the cycleway.

The diagram is useful for a quick cluster analysis, for example to identify agglomerations of positive or negative perceptions in different categories and in relation to sensor data. For example, between ca. 4 and 4.5 minutes, the accelerometer data shows several peaks, one at more than 70 m/s^2, which is possibly related to road bumps. However, the perception of the bike infrastructure remains fairly positive. While the visualisation alone does not provide sufficient information to explain this anomaly, it helps identify the phenomenon. Once identified, a more detailed examination and interpretation of perception data and related cycling events could be carried out.

3.6. Data interpretation

The rating, categorisation and visualisation of collected data can help identify certain phenomena, aggregations, or apparent anomalies. However, it does not provide details about their meaning or relationships. For example, it does not provide a comparison of cycle events and categories. In this section, we discuss two examples of cycle events identified by our test cyclist on the Papanui Parallel MCR (Table 2). These two examples illustrate the detail that is provided as a result of our mixed method approach.

The first example – identified in the above visualisation discussion (Figure 8) – relates to similar peaks in accelerometer data, which were likely to relate to road bumps. These bumps were sometimes perceived as negative, and at other times were not. For example, at 6:43 video time, when riding over a bump, the test cyclist was recorded as saying "Oof – there was a bump" and rated the experience 4 (negative) in the post-cycling review. The accelerometer data showed a peak around 30 m/s^2. The video footage showed an odd design detail where a drainage kerb cut through the cycleway to connect disjointed street gutters (Figure 9).

In comparison, in a second cycle event at 4:08 video time, a similar peak showed up in the accelerometer data and the test cyclist made the following comment: "They [speedbumps] make the cars go really slower [sic]. Which is nice when you share the road", and was rated 2 (positive). While the intensity of "bumpiness" was almost the same in both events, the perception was quite different.

Comparing these two cycling events, in the first event the intensity of the bump comes as a surprise to the cyclist. In the second example, the test cyclist, however, does not complain about the bumpy road and instead embraces the perceived safety and the benefits that speedbumps may provide for cyclists on a shared street. We conclude that bumps may be acceptable, even appreciated, if they are perceived as beneficial and designed for a purpose. However, bumps with comparable intensity that take a cyclist by surprise and do not appear to have a purpose are perceived negatively. The comparison shows the advantage of combining different types of data for interpreting the quality of cycleway infrastructure and emphasises that conclusions cannot be drawn from (objective) sensor-based data alone. It also shows that while the addition of data about cyclists' perceptions is meaningful, even more contextual detail is revealed when this occurs in combination with video.

In the second example, we compare three events of the same category (WAYF). In the first event, at 1:41 video time, where there was clear on-road signage indicating a 2-way-lane, the test cyclist commented: "There are signs everywhere. That is very nice. Like signs on the road" and rated the event as 2 (positive) on the Likert scale. The corresponding video data showed clearly visible signage on the cycleway including bicycle symbols, arrows to indicate directions, green colour indicating that this is a cycle lane, and changes of colour (red) and zebra stripes at a pedestrian crossing. Likewise, in the second event, when the cycle path began, the test cyclist commented: "I like the green colour on the ground. It really helps if you cycle here for the first time" and rated this as 2 (positive) on the Likert Scale. As in the previous example, on-street signage including signalling colours provided effective way-finding support for cyclists.

In the third event, right after crossing a busy street at a traffic light (ca. 3:10 video time), the direction of the cycleway was unclear. The video data showed no on-street signage, but a cycleway signpost indicating the direction of the Major Cycleroute. However, the signpost could be easily overlooked by the cyclist, particularly in a situation where the attention was directed towards crossing the busy road. The test cyclist commented: "Ok, so, here I think it's not clear where to ride at the beginning if you don't know where you've got to go as a bike, but you figure it out quite soon", and rated the event as 4 (negative) on the Likert scale.

Comparing these three events shows that on-road signage, symbols and signalling colours are effective for way-finding; more effective than signposts that can be easily overlooked. Consequently, in this situation, it would be useful to have additional on-road signage to indicate the main cycleway direction.

4. Discussion

The proposed methodology responds to calls for more bottom-up consultation with cyclists and making use of their expertise, perceptions and experiences to improve the design and implementation of urban cycleway infrastructure, and to address the "bike-lash" phenomenon. The stakeholder involvement process allowed us to tap into the knowledge of relevant stakeholders, which was vital to identify the current research focus. The low-cost use of compact mobile devices meant that bicycle-based data collection could be carried out not only by professional researchers but also volunteers and regular cyclists. This is particularly relevant in the context of community-based research or “citizen science” (Bonney et al. 2014) where amateur researchers help collect and analyse data. It also helps to bridge the usual detachment between professional researchers and concerned citizens and could become a pedagogical opportunity for social learning for volunteers and researchers. In addition, many people already own a bicycle and a smartphone, and the appropriate software to read and export sensor data is freely available (such as the AndroSensor mobile application we used). Therefore, the low costs make the methodology potentially accessible in environments where funding is very limited. The costs of 360-degree cameras are still high; however; they continue to fall as the technology evolves. Hence, overall, bicycle-based data collection could become more widespread than it is today.

There are a number of limitations and strengths associated with this research. For the purpose of this study, we collected and interpreted limited data to explore our method. Further testing with multiple cyclists at different times of the year, and in different places is recommended. Data collection with multiple cyclists on the same cycleway might make use of baseline sensor data to reduce the amount of data to be processed. The recorded audio data consisted mainly of shorter comments and situational reactions. The quality and length of comments depended on the test cyclist as there was no interviewer present. This is a potential strength and weakness of our method. We chose quantitative post-cycling ranking (Likert) to operationalise perception data in combination with sensor-based data. This approach was more time-efficient than in-depth interviews. However, it did not produce in-depth qualitative post-event reflections from the test cyclist such as “lived meanings” or experiential values with regard to cycle events, the infrastructure or the landscape context. Interviews could be undertaken with cyclists after their cycle trip to produce detailed contextualised narratives about cycling experiences. These could be a useful addition to our method and yield potentially rich data. However, it was beyond the scope of our study to implement this research step.

In the pilot study, we tested equipment, software and ways to collect data. Thanks to the testing, the actual data collection in the field was a relatively smooth process. However, other parts of the research process were very time consuming. For example, data had to be transcribed and then reflected upon and assessed together with the test cyclist. In the future, software solutions such as advanced voice recognition might speed up parts of the process. However, the individual reflective evaluation of audio and video data cannot be replaced easily. Other time-consuming activities included manual data adjustments, for example overlaying different time stamps from sensor recordings and camera data. This could be less time consuming if GPS data or a real time clock were used to synchronise data. In addition, the manual alignment of categorised perception and sensor data into one spreadsheet was time-intensive. The combined visualisation of different types of data also required advanced programming and coding skills and the built-in chart modules that come with regular software packages such as Microsoft Excel did not enable the data to be visualised as we envisioned. Such processes need to be streamlined with the help of appropriate software solutions to enable the widespread application of the method.

5. Conclusions

This paper responds to stakeholders' needs to explore a user-centred, low-cost approach to capturing data regarding urban cycling infrastructure. It lays methodological foundations for analysing, assessing, and improving urban cycleways based on users' perceptions and infrastructure monitoring. Testing at a larger scale and the development of automated data analysis processes could improve the effectiveness. Methodological additions that produce more comprehensive experiential accounts could be incorporated in any future research. The proposed methodology could also potentially be extended beyond cycleway performance research with opportunities to develop similar approaches for other types of infrastructure. We hope that our approach encourages stakeholders to collect their own user-generated data and interpret the data to support the planning, design and implementation of urban cycleways.

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Notes

1. For an illustration regarding axis representation (x, y, z) and movement of bicycles along their three axes (roll, pitch, yaw) see (Joo and Oh 2013, 5).
2. Using global coordinates, the z-axis always shows a base value around 9.81 m/s^2 (acceleration due to the force of gravity on Earth) when there is no movement.