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Can providing safe cycling infrastructure encourage people to cycle more when it rains? The use of crowdsourced cycling data (Strava)

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ABSTRACT

Many local authorities in the UK and other developed countries have spent a substantial amount of time and money providing safe cycling infrastructure to improve cycling environments. However, it is not clear whether these expensive physical investments are an effective strategy to encourage people to cycle more in cities where there is a high level of precipitation. The evidence is limited, partly due to data limitations. We used crowdsourced cycling data (taken from the Strava activity-tracking app) and fixed-effects panel regression models to investigate whether providing safe cycling infrastructure could be an effective way to overcome adverse weather conditions. We selected the city centre of Glasgow, Scotland because of the current size and scope of investments. We found that providing safe cycle paths could encourage people to cycle more, especially on dry days. However, findings suggested that rainy cities like Glasgow may not have realised the full benefits of safe cycling infrastructure because there are larger reductions in the volume of cycling on rainy days on these routes. Planners, especially from cities with a high level of precipitation, should consider how to improve cycle paths to overcome adverse weather and other policies (e.g., providing shower facilities at workplaces, incentives to cycle, etc.) to increase cyclists' resilience to bad weather.

1. Introduction

The benefits of cycling have been well documented. It can reduce car-dependency, traffic congestion, air pollution and improve public health (Celis-Morales et al., 2017; Christensen et al., 2012; Kim, 2019; Oja et al., 2011). Due to the significant health and environmental benefits, many local authorities in the UK have tried to encourage cycling. In 2010 the Scottish Government set out an ambitious vision of having 10% of everyday journeys being made by bicycle by 2020. Although they have conceded this won't be achieved, local governments have implemented various measures since 2010 to increase cycling mode share.

One of these measures is to provide safe cycling infrastructure such as segregated cycle lanes. Evidence from previous qualitative and quantitative studies has shown the importance of building safe cycle paths to improve the cycling experience and encourage people to cycle more (Hong et al., 2019; Scott and Span, 2009). In addition, a body of land-use/travel-behaviour studies have shown the importance of built environments in shaping travel behaviour (Ewing and Cervero, 2010; Ewing et al., 2015; Hatamzadeh et al., 2019; Hong et al., 2014). This is unsurprising. However, what is not evident is whether these expensive infrastructure investments encourage people to cycle in adverse weather conditions.

Many Scottish cities have a reputation for poor weather conditions, especially during winter (e.g., heavy rainfall), and weather is

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known to be one of the most important determinants of daily transport mode choice (Böcker et al., 2016). Therefore, it is critical for planners and policy makers to understand if investing in cycling infrastructure mitigates the negative effects of poor weather conditions and increases cycling in Scotland across the whole year.

Unfortunately, empirical studies are scarce, partly due to data limitations. Some empirical studies used cycling data from sensors (e.g., pneumatic tubes) to examine the relationship between weather and cycling (Miranda-Moreno and Nosal, 2011; Thomas et al., 2013; Zhao et al., 2018). These data are appropriate to analyse this relationship. However, they are less appropriate to investigate how the relationship varies according to the type of cycling infrastructure because typically only a small number of sensors are installed in fixed locations. Generally, the locations selected are popular routes; often with good infrastructure. The widespread ownership and use of smartphones with GPS sensors have given rise to crowdsourced cycling data which provides a new opportunity for planners and researchers to look at cycling activities at fine geographic and temporal scales.

This study aims to investigate the relationship between cycling, weather, and infrastructure using data collected from the activity-tracking app Strava in 2016, information on the location of cycling infrastructure, and hourly weather data. Specifically, two research questions were considered: (1) Do safe cycle routes make a difference to cycling volumes? and; (2) Does providing safe cycling infrastructure (i.e., segregated lanes and shared off-road lanes) encourage people to cycle more on rainy days? For the analyses, we chose the city centre of Glasgow as the study area for two reasons. Firstly, for several years, Glasgow City Council (GCC) has made substantial investments to expand the provision of cycling infrastructure in and around the city centre. Currently, they are investing approximately £115 million within the city centre to build integrated networks for pedestrians and cyclists. The size and scope of this investment makes the city an interesting case study. Secondly, a body of studies, outlined in the literature review, has shown the value of Strava data for cycling research. However, some studies indicated that its potential value will be higher in urban areas such as city centres where the intensity of cycling is high. Therefore, this study focused on the city centre of Glasgow. Fixed-effects panel models are used to quantify and test the relationship between cycling, infrastructure, and weather.

2. Literature review

The benefits of regular walking and cycling have led researchers from a variety of disciplines to investigate how to increase levels of active travel. For example, studies have been published in the fields of transport (Buehler & Dill, 2016; Hong et al., 2019), urban planning (Ewing and Cervero, 2010; Kim et al., 2018) and public health (Besser and Dannenberg, 2005; Le et al., 2018). Cycling has been a particular focus because it is often seen as a viable alternative to trips by private cars given that many car trips are relatively short. In the 2014 Scottish Household Survey, for example, around 60% of car trips are less than 5 miles. This is consistent with some states in the US (Resource Systems Group, 2015). Many of those trips could presumably have been made by bicycle. GCC produced a cycling network map in their strategic plan for cycling, showing that most areas in the city of Glasgow can be reached in 30 min by bicycle (Sustrans, 2015).

One important idea in the literature is that a key reason people don't cycle is that they face barriers. In our study, we focus on adverse weather and a lack of safe routes as barriers. Several other potential barriers have also been considered (Christie et al., 2011; Salmon et al., 2007). Bauman et al. (2008), for example, listed personal factors (e.g., poor health, lack of skills and time), social and cultural factors (e.g., gender, deprivation), built environment factors (land-use, bicycle parking, bicycle paths), safety, and policy and regulation as barriers to cycling. Whereas Pooley et al. (2011) argued that the complexities and contingencies related to daily travel should be addressed to increase the level of walking and cycling. Several other studies showed that travel distance, comfort, cost, parking, perceptions and other social and individual level factors are key barriers to cycling (Gatersleben and Appleton, 2007; Manaugh et al., 2017).

2.1. Natural environments

Adverse weather and lack of safety are commonly cited barriers to cycling. A number of studies have identified the importance of natural environment factors such as temperature, precipitation and humidity on cycling activities across different cities (El-Assi et al., 2017; Eren and Uz, 2019; Helbich et al., 2014). For example, Miranda-Moreno and Nosal (2011) utilised data from five automatic counters and examined the relationship between weather conditions and cycling ridership in Montreal, Canada. Their analysis showed significant effects of precipitation, temperature, and humidity on cycling volumes. An et al. (2019) used data from the Citibike public bicycle sharing programme (PBSP) in New York and investigated the effects of weather conditions on cycling activities. They found that weather had a stronger impact on cycling compared to topography, land use and other temporal factors. Although they examined the potential interactions between weather and infrastructure, their analytical units were community districts rather than roads, introducing a potential source of bias into their analysis. Motoaki and Daziano (2015) conducted an online survey of staff and students at Cornell University, New York, USA, and found significant relationships between weather conditions and cycling. Specifically, as the level of precipitation increases, people are less likely to cycle.

Given that countries with higher levels of cycling are likely to have a higher proportion of skilled cyclists, we may expect the impacts of precipitation on cycling to vary by country. For instance, there are more skilled cyclists in countries such as the Netherlands where cycling plays a significant role in transport systems. Although some studies found less profound effects of precipitation on cycling (Helbich et al., 2014; Rietveld & Daniel, 2004), studies from other countries such as Germany, Canada, the United Kingdom, Australia, Sweden and the Netherlands still found significant effects of rain on cycling (Bergström and Magnusson, 2003; Böcker et al., 2013; Goetzke and Rave, 2010; Nankervis, 1999; Parkin et al., 2008; Saneinejad et al., 2012; Winters et al., 2007). This may hint that precipitation still influences cycling behaviour, but that the negative effects could be smaller in cities with a high level of cycling.

Some studies also indicated that weather effects vary according to trip purposes (Helbich et al., 2014; Thomas et al., 2013). In particular, recreational trips are more sensitive to bad weather conditions than utilitarian trips, possibly due to the flexibility of recreational cycling. Overall, it is evident that weather is a crucial factor that should be considered when making plans in cities with a high level of precipitation.

2.2. Cycling infrastructure (Built environments)

Manaugh et al. (2017) investigated the relative importance of different barriers to cycling and compared how they differ according to socio-demographic groups by utilising a mixed-methods approach. Although their survey data only included staff and students at McGill University in Montreal, Canada, their analysis showed that safety and effort are the most commonly cited barriers to cycling for potential cyclists (i.e., those who do not currently cycle but have a strong desire to cycle). One of the solutions to improve safety is to provide safe cycle paths.

A handful of studies has indicated the important role of cycling infrastructure on cycling activities as well as safety. Specifically, several empirical studies showed the positive impacts of cycle paths on the level of cycling activity, implying that installing cycling infrastructure could encourage people to cycle more (Buehler & Pucher, 2012; Hong et al., 2019). Moreover, some suggested that providing cycling infrastructure could improve the level of safety, thereby increasing the level of cycling activities (Christensen et al., 2012; Heinen et al., 2010).

There are also empirical studies examining interactions between built environments and the effects of bad weather on cycling (Miranda-Moreno & Nosal, 2011; Phung & Rose, 2008). Specifically, Helbich et al. (2014) showed that developed areas are less affected by precipitation than less developed areas and this could be due to the availability of shelters and long travel distances of cyclists from remote areas.

2.3. Personal characteristics

Personal characteristics play an important role, both in themselves and in the way they interact with the physical and natural environment. Aldred and Jungnickel (2014) emphasised the role of cycling cultures in shaping cycling practices in four UK cities, and Muñoz et al. (2013) highlighted the importance of habit in the decision to cycle to work.

Socio-demographic characteristics, attitudes, perceptions and social norms are also found to be influential factors for cycling (Heinen et al., 2011; Piatkowski and Marshall, 2015; Prillwitz and Barr, 2011). For example, Sallis et al. (2013) indicated that young white men cycled more than other groups. Interestingly, their analyses also showed that improving safety from traffic could lead to substantial increases in riding frequency, especially for minority groups.

Emond et al. (2009) showed the differences in perception of safety between male and female cyclists, and highlighted the need of planning processes to take gender differences into account. Collectively, these studies imply that planners should consider the diverse needs of different socio-demographic groups to make more effective cycling plans.

The experience of cyclists and trip characteristics have been shown to play an important role in determining the relationship between cycling and weather. For example, Motoaki and Daziano (2015) showed that adverse weather effects become stronger for less-skilled cyclists compared to skilled cyclists. Although Amiri and Sadeghpour (2015) found a large reduction in cycling frequencies during the winter period, a high portion of their respondents (mostly frequent cyclists) were not sensitive to cold temperature. Bergström and Magnusson (2003) collected two surveys in 1998 and 2000 for employees in two Swedish cities to examine bicycle trips to workplaces. Their data showed that winter cyclists own fewer cars compared to other types of cyclists (e.g., summer-only cyclists and non-cyclists) and commute shorter distances. In addition, improving road conditions could encourage summer-only cyclists to cycle during the winter period.

2.4. Summary

In sum, previous studies emphasised the importance of safe cycle paths and weather conditions in determining cycling demand. However, empirical research about how cyclists who use different types of cycling infrastructure react to weather conditions is scarce.

One of the reasons for the lack of studies may be the lack of appropriate data. As indicated, most of the empirical studies about weather effects used data from sensors (Miranda-Moreno & Nosal, 2011; Thomas et al., 2013) or ridership data form bike sharing programmes (An et al., 2019; Kim, 2018). These types of data are generally from fixed locations, limiting geographic scale and coverage of different types of cycling infrastructure.

Some research utilised household or travel surveys to investigate the association between weather conditions and cycling behaviour (Goetzke & Rave, 2010; Helbich et al., 2014). However, we believe this is only possible for certain countries such as the Netherlands where the population of cyclists is very large. For example, only 1–2% of the total population cycle in Scotland, limiting sample sizes for the analysis of cycling patterns with a national travel survey.

3. Methodology

Our main aim is to measure how weather affects cycling volumes on streets, and how this effect may vary depending on the type of street and whether there is any cycling infrastructure present. Although our data does not allow us to include personal characteristics of the cyclists in our analysis, we do not adopt an environmental deterministic perspective where we assert that such characteristics are unimportant. Rather, we adopt the position of probabilism, whereby the built environment is seen as providing a framework of incentives which encourage certain behaviours while discouraging others (Næss, 2015).

3.1. Study area

We take the city of Glasgow, Scotland as our case study. The city, the largest in Scotland, is well suited to addressing our research questions due to its weather conditions and the investments in cycling infrastructure which have been made. For example, GCC installed cycling infrastructure on several routes (e.g., West City Way and South West City Way) to prepare for the 2014 Commonwealth Games and improve the environment for cyclists (Hong et al., 2019). It is expected that this effort will continue in the UK regardless of the substantial costs due to the benefits which have been demonstrated of this sort of investment.

3.2. Data

New forms of cycling data, e.g., from activity-tracking apps such as Strava, present new opportunities for researchers. Although such crowdsourced data have been criticised for issues such representativeness and having a low number of users, many studies have validated its usefulness in cycling research (Hochmair et al., 2019; Jestico et al., 2016). For example, Hong et al. (2019) compared 2014 cycling counts from Strava with 2014 cordon counts (manual cycling count data from 38 locations around the city centre) in Glasgow and found very high correlations between them. In addition, their analyses showed the significantly improved correlations (up to about 0.9) as the level of temporal aggregation of the data increases (e.g., hourly to daily). Jestico et al. (2016) also compared Strava data with manual counts in Victoria, British Columbia and argued that Strava data are useful to map spatial variations in cycling patterns, especially in urban areas. Based on results from the above studies, several empirical studies have used Strava data to examine cycling behaviour (McArthur and Hong, 2019; Sun et al., 2017)[1].

Three data sources were used for this study. Firstly, Strava data for 2016 in the Glasgow area was used to calculate hourly total counts of Strava trips. To do this, we selected all roads in the city centre area (Fig. 1) and used link-level, minute-by-minute cycling counts from Strava. For the statistical analyses, we calculated average hourly counts by type of cycling infrastructure (i.e., bus corridors, calm/low traffic roads, demarcation on road, segregated lanes, shared off road, signed on road and nothing on road). In addition, the average total distance cycled on each type of infrastructure was calculated (i.e., average of the sum of hourly total cycling counts for a link multiplied by the length of the link (km)). This form of aggregation avoids the problem that the number of trips counted on a road will depend on the arbitrary number of edges used to represent that road in a GIS.

We used the cycling infrastructure type as an analytical unit because there are an extremely high number of roads in the city, many with no cycling activity, making it hard to use statistical models with the edges as observational units. In addition, our main focus is to examine whether safe cycle routes such as segregated lanes or shared off-road routes could better overcome adverse weather conditions compared to unimproved roads. Therefore, using the infrastructure type as an analytical unit makes the analyses more straightforward. In addition, we included only cycling activities taking place between 6:00 am and 10:59 pm.

Secondly, we used weather data from Glasgow with the same temporal coverage as the cycling data. For the analyses, we selected days with complete hourly weather data during the study period. For the analyses, we considered rain/snow[2] and temperature. Lastly, we used cycling infrastructure data from GCC. The data include the name of the infrastructure, completion dates, as well as the type of infrastructure. We utilised ArcGIS to manually match infrastructure data with the Strava data (which is represented on an OpenStreetMap network). After removing all missing values and two days which contained some roads with implausibly high cycling volumes, we have a total of 34,034 observations (i.e., 7 types of cycling infrastructure * 286 days * 17 h (6:00 am–10:59 pm)).

Table 1 shows the descriptive statistics. About 20% of days in 2016 had rain, and the average temperature was 9.2 °C. About 90% of all road segments in Glasgow's city centre do not have any cycling signs on the roads. Around 2.7% of road segments have calm/low traffic and about 3.6% of segments have safe cycling infrastructure (segregated + shared off road). Strava Metro provided aggregated information on the gender and age of the users. These statistics pertain to whole Glasgow area rather than just the city centre. It shows that around 85% of Strava users are male, and most of them are aged between 25 and 54. The Strava and weather data were obtained from the Urban Big Data Centre at the University of Glasgow. Data are available upon application (https://www.ubdc.ac.uk/).

3.3. Analytical method

The main objective of this paper is to investigate how cycling volumes vary with weather, and how this relationship varies on different types of infrastructure in a city with an average annual rainfall of 1079 mm. Our data have a panel structure and we employed a fixed-effects linear regression model with interaction variables to test our hypothesis. The reduced form of the model can be written as follows:

[1] Several empirical studies using Strava data in Glasgow already showed very high correlations between Strava data and cycling count data (cordon counts and annual average daily flow data from the UK DOT). Therefore, we strongly believe 2016 Strava data are valid for our analysis.

[2] Snow days are only 2% of total days. Therefore, we refer all precipitation as rain.

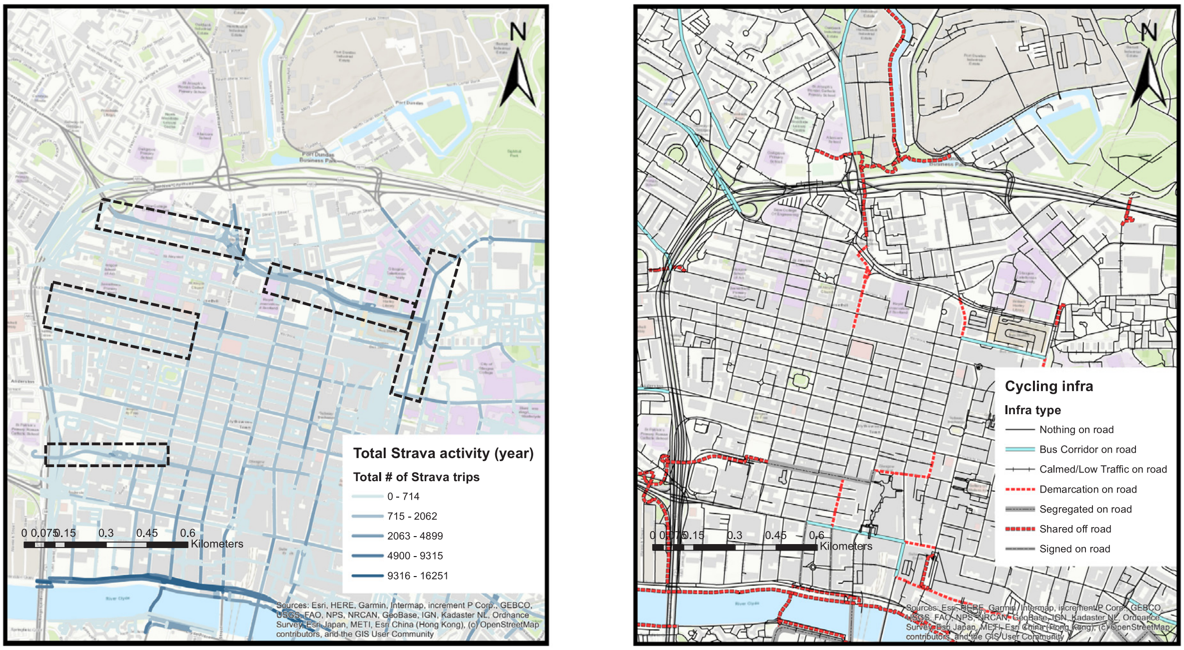

Fig. 1. Total cycling activity level (# of Strava trips) in 2016 and cycling infrastructure in the study area.

Table 1
Descriptive statistics.

	Percentage	SD		Total
Weather			**Socio-demographics**	
Rain	19.334%		Male (Under 25)	847
Temperature*	9.222	5.251	Male (25–34)	2332
			Male (35–44)	3316
Infrastructure			Male (45–54)	2675
Nothing on road	90.306%		Male (55–64)	720
Bus Corridor	1.023%		Male (Over 65)	120
Calmed/low traffic	2.747%		Male (No age info)	3075
Demarcation	1.837%		Female (Under 25)	207
Segregated	1.255%		Female (25–34)	544
Shared off road	2.372%		Female (35–44)	456
Signed on road	0.459%		Female (45–54)	337
			Female (55–64)	78
			Female (Over 65)	5
			Female (No age info)	580

* It is an average for the continuous variable.

$$\sqrt{y_{hdmi}} = \alpha + \beta_{\mathrm{temp}}x_{temp\_\mathrm{hdm}} + \beta_{\mathrm{rain}}x_{\mathrm{rain\_hdm}} * \beta^{\mathrm{T}}_{\mathrm{infra}}x_{\mathrm{infra}} + \beta^{\mathrm{T}}_{\mathrm{dayofweek}}x_{\mathrm{dayofweek\_d}} + \gamma_h + \eta_m + \nu_i + \varepsilon_{hmi}$$

where y_{hdmi} is the average hourly cycling counts (or average cycling distances) in hour h, day d, month m and for infrastructure i. x_{temp_hdm}, x_{rain_hdm}, x_{infra} *and* $x_{\mathrm{dayofweek\_d}}$ represent temperature, rain, different types of cycling infrastructure and the day of the week, respectively. $\gamma_{h,}\eta_m$, *and* ν_i are the fixed-effect parameters, and ε_{hmi} is the error term that is assumed to follow a normal distribution. We took the square root of y_{hdmi} due to its skewed distribution and the fact it has some zero values. We also tried an inverse hyperbolic sine transformation which gave consistent results. It should be noted that these transformations do not resolve the skewedness completely due to the characteristics of the cycling data.

As an additional robustness check, we created two additional samples: (1) one with popular routes (i.e., the total cycling activity level in 2016 is above the median total cycling activity level from all roads in 2016); and (2) one restricted to commuting hours (7:00 am to 9:59 am & 4:00 pm to 6:59 pm). These additional analyses will show us if the results are consistent regardless of the popularity of the routes and the travel purposes.

4. Results

Fig. 1 shows the total cycling activity level in 2016 per link and cycling infrastructure in the study area. We can see that roads

Table 2
Average cycling volumes (# of Strava trips) and cycling distances (km) per link per month made by Strava users.

Month	Total		Popular roads		Commuting time periods	
	Avg.counts (#Strava trips)	Avg.distances (km)	Avg.counts (#Strava trips)	Avg.distances (km)	Avg.counts (#Strava trips)	Avg.distances (km)
Jan	0.096	0.004	0.187	0.009	0.184	0.009
Feb	0.110	0.005	0.213	0.010	0.217	0.010
Mar	0.169	0.008	0.330	0.016	0.340	0.016
Apr	0.183	0.009	0.357	0.017	0.360	0.017
May	0.233	0.011	0.455	0.021	0.456	0.021
Jun	0.257	0.012	0.504	0.024	0.524	0.024
Jul	0.201	0.009	0.394	0.019	0.402	0.019
Aug	0.229	0.011	0.448	0.021	0.467	0.022
Sept	0.212	0.010	0.412	0.019	0.447	0.021
Oct	0.200	0.009	0.390	0.018	0.413	0.019
Nov	0.163	0.008	0.317	0.015	0.333	0.015
Dec	0.094	0.004	0.183	0.009	0.181	0.008

close to the River Clyde are the most popular routes for Strava users. Amenity is one of the most important determinants of cycling route choice (Fraser & Lock, 2011). In addition, most of these roads are shared off-road cycle paths, which are safer than other types of roads. Besides, these routes are very flat and connect the east, west and south areas of Glasgow to the city centre. We can also see relatively high volumes of cycling in the areas highlighted with boxes in Fig. 1 (left panel) which connect the east, north and west areas of Glasgow to the city centre. This demonstrates that our data produce reasonable cycling patterns in our study area.

Table 2 shows the average cycling activities per link per month for the three different samples (i.e., total, popular roads and trips during commuting times). The seasonal patterns are evident. The average cycling counts per link per month is the highest in June and lowest in December. In addition, there are higher cycling volumes in the commuting sample than the other two. The highest average cycling counts per link per month is 0.524. That means there are many links with very little or no cycling by Strava users. This is to be expected given that only 1–2% of people cycle in Scotland. This also justifies why we did not use links as the analytical unit.

Fig. 2 shows how cycling on different types of infrastructure varies over the course of 2016. Again, a strong seasonal effect is evident, confirming the importance of controlling for it in the analyses. As expected, safe cycle paths such as shared off-road and segregated lanes have much higher volumes of cycling activities made by Strava users than typical roads (i.e., *Nothing on road*). Interestingly, roads with bicycle signs also has a high level of cycling. Considering that our study area is a city centre, there are only a small number of signed roads (about 0.46% of the links), and all signed roads are flat, the result makes sense. These simple graphs show that providing safe cycling infrastructure could make a difference to the volume of cycling. In addition, they show that safe cycle paths have larger variations in the volume of cycling across the year than typical roads. This hints that casual cyclists use safe cycle paths more during spring, summer and autumn when there is mild weather in Glasgow.

To further examine both the relationship between weather and cycling, and how the relationship may vary depending on the type of infrastructure, we utilised fixed-effect linear regression models with interaction variables. Results are presented in Table 3 (average cycling counts) and Table 4 (average cycling distances). Since the types of cycling infrastructure are time invariant, our model cannot estimate the coefficients for different types of cycling infrastructure. However, Fig. 2 shows that safer cycle paths have higher volumes of cycling activities made by Strava user than typical roads as expected. All control variables show results consistent with previous studies. Rain has a negative effect for both average cycling counts and cycling distances, indicating the negative effect of bad weather conditions on cycling. Specifically, rain is associated with the average number of cycling counts made by Strava users on typical roads (*Nothing on road*) decreasing by 0.07 multiplied by the current average number of activities[3]. On the other hand, as the temperature increases the level of cycling activities also increases. Although high temperatures could discourage cycling, the average summer temperature in Glasgow is mild, e.g., below 20 °C.

Compared to Sundays, cyclists make more trips on weekdays. Our analyses identify significant seasonal effects. Strava users make more trips during spring, summer and autumn compared to winter. The level of cycling activities peaks during the summer (Jun–Aug). Fig. 2 also confirms this result. As expected, our model shows significant hourly variation in average cycling counts and distances. There are more cycling activities in the morning and evening peaks. This is because of commuting trips made by Strava users.

Finally, we found that there are larger reductions in average cycling counts and cycling distances on safer cycle paths (i.e., *Segregated* and *Shared off-road*) than typical roads (i.e., *Nothing on road*) when it rains. Interestingly, there are no significant interaction effects for *Signed on road* and *Demarcation* that also have high cycling volumes (see Fig. 2). This result implies that cyclists who use safe cycle paths are more vulnerable to bad weather conditions, and previous studies imply that these people are highly likely to be less-skilled cyclists (Motoaki & Daziano, 2015). Skilled cyclists may use more direct routes to the destinations, even if they are typical roads or roads with bicycle signs regardless of weather conditions.

As discussed, there are many roads with little or no cycling by Strava users. Therefore, we tested if our results are consistent when we only compared popular roads or cycling activities during commuting time periods. The results are shown in Tables 5 and 6. They

[3] Marginal effect ($dY/dX_{\text{rain\_hdm}}$) *equals to* $2\beta_{\text{rain}}\widehat{Y}$.

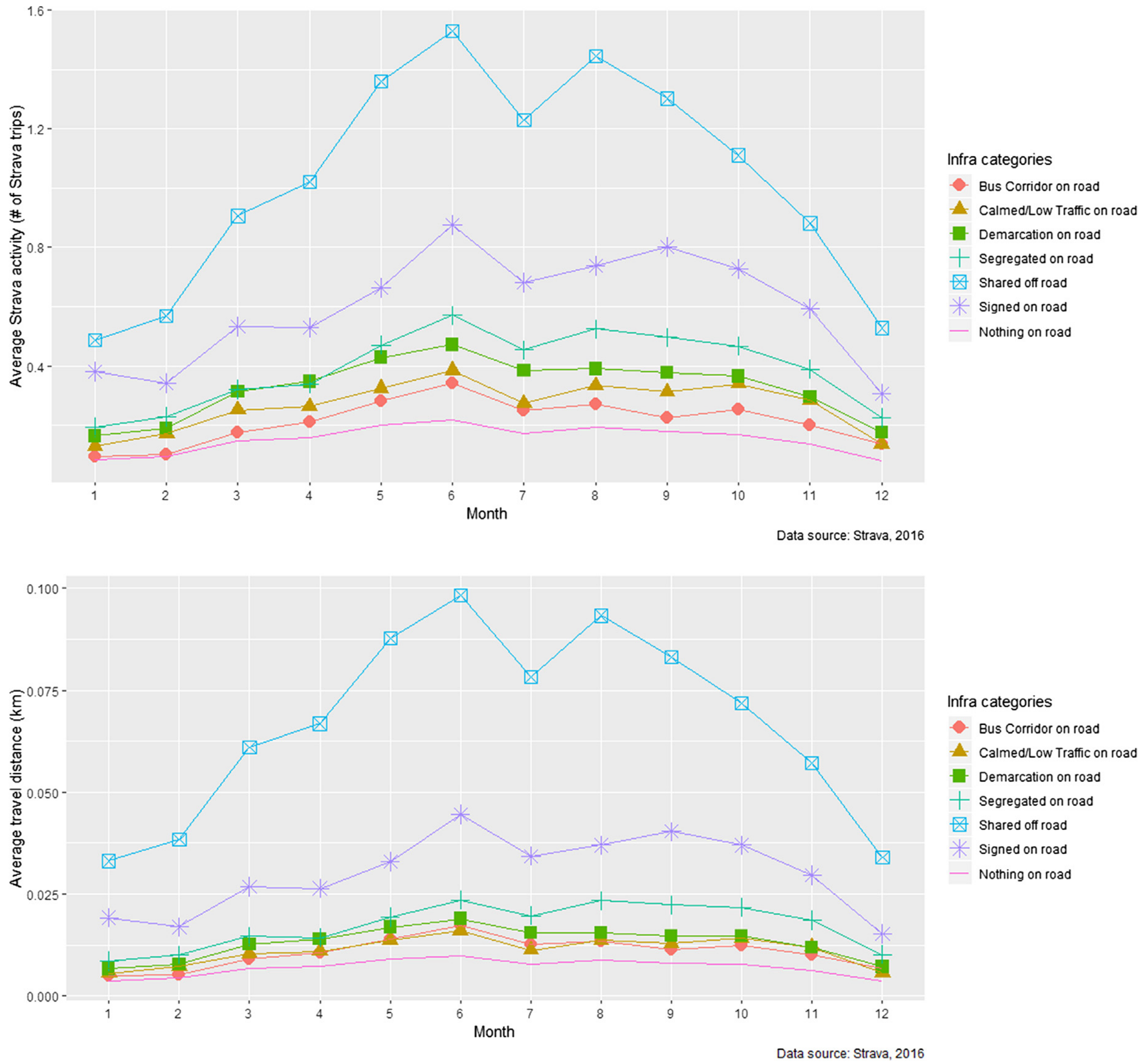

Fig. 2. Average total cycling volumes (# of Strava trips) and cycling distances according to cycling infrastructure types.

confirm that our results are consistent regardless of the popularity or the purpose of trips (commuting vs. non-commuting) although commuting trips are less sensitive to rain as previous studies found.

5. Conclusions

The importance of providing safe cycling infrastructure to encourage people to cycle more has been acknowledged through several qualitative and quantitative studies. Many local authorities in the UK have expended significant effort, time and money to build safe cycling paths in their cities. Although there are many benefits of cycling infrastructure such as safety, walkability and livability of streets, its positive impacts on the cycling activity might be reduced in cities with high precipitation levels. This study utilised crowdsourced cycling data (from the Strava app) to examine: (1) whether safe cycle paths affect the level of cycling activities; and (2) whether providing safe cycling infrastructure could be an effective way to mitigate the effects of adverse weather conditions. Our analyses focused on the city centre of Glasgow and the results have several policy implications.

First, our data (Fig. 2) show that there are higher levels of cycling by Strava users on safe cycle paths (e.g., *Shared off-road, Segregated on road*, etc.) compared to typical roads (i.e., *Nothing on road*). This result is consistent with previous studies and indicates that providing safe cycle paths encourages people to cycle more.

Second, our results found two significant temporal variations. There are two peaks in a day. This is because of commuting trips. There are also significant seasonality effects. The level of cycling activities peaks in summer and decreases in winter. This demonstrates the importance of weather conditions on cycling. There are high levels of precipitation during the winter, and around ten

Table 3
The result from a fixed-effects linear regression model for average cycling counts per infrastructure.

	Estimate	SE	t-value	P-value	
Weather					
Rain (rain = 1)	−0.035	0.011	−3.108	0.002	**
Temperature	0.007	0.001	11.189	0.000	***
Day of week (ref = Sun)					
Mon	0.253	0.006	40.945	0.000	***
Tue	0.298	0.006	47.683	0.000	***
Wed	0.288	0.006	45.372	0.000	***
Thu	0.269	0.006	43.628	0.000	***
Fri	0.222	0.006	36.068	0.000	***
Sat	−0.003	0.006	−0.538	0.591	
Month (ref = Jan)					
Feb	0.029	0.008	3.767	0.000	***
Mar	0.086	0.008	11.214	0.000	***
Apr	0.125	0.008	15.499	0.000	***
May	0.158	0.009	16.888	0.000	***
Jun	0.169	0.012	14.009	0.000	***
Jul	0.118	0.010	11.312	0.000	***
Aug	0.156	0.011	14.192	0.000	***
Sept	0.130	0.010	12.888	0.000	***
Oct	0.139	0.009	15.778	0.000	***
Nov	0.118	0.008	15.172	0.000	***
Dec	−0.014	0.008	−1.885	0.059	.
Hour (ref = 6 am)					
7am	0.433	0.010	44.500	0.000	***
8am	0.650	0.010	66.705	0.000	***
9am	0.254	0.010	25.973	0.000	***
10am	−0.011	0.010	−1.076	0.282	
11am	−0.024	0.010	−2.465	0.014	*
12 pm	−0.004	0.010	−0.375	0.708	
1 pm	−0.030	0.010	−2.948	0.003	**
2 pm	−0.044	0.010	−4.336	0.000	***
3 pm	0.023	0.010	2.258	0.024	*
4 pm	0.277	0.010	27.687	0.000	***
5 pm	0.564	0.010	56.718	0.000	***
6 pm	0.291	0.010	29.440	0.000	***
7 pm	0.031	0.010	3.192	0.001	**
8 pm	−0.086	0.010	−8.808	0.000	***
9 pm	−0.154	0.010	−15.817	0.000	***
10 pm	−0.223	0.010	–22.898	0.000	***
Interactions (ref = Nothing on road)					
Rain:Bus corridor	−0.023	0.016	−1.481	0.139	
Rain: Calmn/low traffic	−0.016	0.016	−0.991	0.322	
Rain: Demarcation	−0.029	0.016	−1.856	0.063	.
Rain: Segregated	−0.057	0.016	−3.638	0.000	***
Rain: Shared off road	−0.122	0.016	−7.721	0.000	***
Rain: Signed on road	−0.025	0.016	−1.578	0.115	
Adjusted R-squared	0.47284				
F-statistic:	745.672				

Significant at the 0.10 level of significance.
* Significant at the 0.05 level of significance.
** Significant at the 0.01 level of significance.
*** Significant at the 0.001 level of significance.

fewer hours of daylight compared to the summer in Glasgow.

Previous studies hint that more experienced cyclists and commuting trips are less sensitive to bad weather conditions. It means that policies encouraging cycling as a commuting mode could be one way to overcome the negative effects of bad weather on cycling (e.g., facilities at work such as showers and bicycle parking and incentive schemes (Wardman et al., 2007)). In addition, female cyclists are more affected by adverse weather conditions than men, and safety is one of the most important barriers for cycling for this group (Garrard, 2003). Therefore, improving safety (e.g., training, regulations, speed limits, well-maintained cycling infrastructure, etc.) could mitigate the effects of bad weather. Interestingly, we can see that safe cycle paths are more sensitive to the seasonality effects. This implies that less-skilled people or casual cyclists use these paths more when weather is better.

Finally, we found that there are negative interactions between rain and safe cycle paths. Safe cycling infrastructure could encourage more people to cycle. This would be especially good for less-skilled or casual cyclists. However, rainy cities like Glasgow may not have realised the full benefits of safe cycling infrastructure in increasing the level of cycling activity because there would be larger reductions in the level of cycling activities on rainy days on these paths. This could be the same reason: less-skilled people are more

Table 4
The result from a fixed-effects linear regression model for average cycling distances(km) per infrastructure.

	Estimate	SE	t-value	P-value	
Weather					
Rain (rain = 1)	−0.007	0.003	−2.801	0.005	**
Temperature	0.002	0.000	10.764	0.000	***
Day of week (ref = Sun)					
Mon	0.056	0.001	38.579	0.000	***
Tue	0.066	0.001	45.261	0.000	***
Wed	0.064	0.001	42.870	0.000	***
Thu	0.060	0.001	41.314	0.000	***
Fri	0.049	0.001	34.093	0.000	***
Sat	−0.001	0.001	−0.625	0.532	
Month (ref = Jan)					
Feb	0.006	0.002	3.375	0.001	***
Mar	0.019	0.002	10.704	0.000	***
Apr	0.027	0.002	14.423	0.000	***
May	0.033	0.002	15.262	0.000	***
Jun	0.036	0.003	12.887	0.000	***
Jul	0.025	0.002	10.333	0.000	***
Aug	0.034	0.003	13.233	0.000	***
Sept	0.028	0.002	11.892	0.000	***
Oct	0.031	0.002	14.881	0.000	***
Nov	0.026	0.002	14.422	0.000	***
Dec	−0.004	0.002	−2.105	0.035	*
Hour (ref = 6am)					
7am	0.095	0.002	41.893	0.000	***
8am	0.142	0.002	62.353	0.000	***
9am	0.054	0.002	23.705	0.000	***
10am	−0.001	0.002	−0.367	0.714	
11am	−0.006	0.002	−2.468	0.014	*
12 pm	0.000	0.002	0.047	0.963	
1 pm	−0.005	0.002	−2.124	0.034	*
2 pm	−0.009	0.002	−3.659	0.000	***
3 pm	0.006	0.002	2.417	0.016	*
4 pm	0.063	0.002	27.077	0.000	***
5 pm	0.130	0.002	55.793	0.000	***
6 pm	0.068	0.002	29.238	0.000	***
7 pm	0.007	0.002	3.213	0.001	**
8 pm	−0.018	0.002	−8.033	0.000	***
9 pm	−0.033	0.002	−14.669	0.000	***
10 pm	−0.048	0.002	−21.222	0.000	***
Interactions (ref = Nothing on road)					
Rain:Bus corridor	−0.005	0.004	−1.478	0.139	
Rain: Calmn/low traffic	−0.002	0.004	−0.505	0.613	
Rain: Demarcation	−0.005	0.004	−1.321	0.187	
Rain: Segregated	−0.011	0.004	−2.882	0.004	**
Rain: Shared off road	−0.034	0.004	−9.198	0.000	***
Rain: Signed on road	−0.006	0.004	−1.746	0.081	.
Adjusted R-squared	0.44644				
F-statistic:	670.605				

Significant at the 0.10 level of significance.
* Significant at the 0.05 level of significance.
** Significant at the 0.01 level of significance.
*** Significant at the 0.001 level of significance.

likely to use safe cycling infrastructure and are more vulnerable to bad weather conditions than skilled cyclists. Therefore, this hints to planners that the current level of safe cycling infrastructure is not enough to overcome bad weather conditions, requiring more comprehensive policy approaches. As indicated in the literature review, it might be necessary to combine land use policies (e.g., compact developments) to encourage people to travel shorter distances and provide more shelter services.

There are some limitations. First, we focused on the city centre area because some studies argued that Strava data are more appropriate for developed areas where the level of cycling is high. Second, a more sophisticated analytical approach is required due to the characteristics of data. There are a number of roads with zero or only small number of cycling activities. This is also because of the small number of total cyclists. This provides some challenges when using statistical models due to the skewedness. Third, our data did not contain any personal characteristics (due to the need to protect privacy). This meant we were unable to study how the response to bad weather was related to the type of cyclist. Finally, although we found the value of Strava data to examine cycling behaviour, it is still possible that data is biased, potentially affecting our findings. Achieving more ground-truth data across different areas will help adjust the potential bias, enabling researchers to do more robust analyses.

Table 5
The result from a fixed-effects linear regression model with samples containing only popular roads.

	Avg. cycling counts per infrastructure			Avg. cycling distances per infrastructure		
	Estimate	P-value		Estimate	P-value	
Weather						
Rain (rain = 1)	−0.067	0.000	***	−0.014	0.000	***
Temperature	0.007	0.000	***	0.002	0.000	***
Day of week (ref = Sun)						
Mon	0.263	0.000	***	0.058	0.000	***
Tue	0.310	0.000	***	0.069	0.000	***
Wed	0.300	0.000	***	0.066	0.000	***
Thu	0.280	0.000	***	0.062	0.000	***
Fri	0.230	0.000	***	0.051	0.000	***
Sat	−0.004	0.477		−0.001	0.420	
Month (ref = Jan)						
Feb	0.031	0.000	***	0.007	0.000	***
Mar	0.091	0.000	***	0.020	0.000	***
Apr	0.131	0.000	***	0.029	0.000	***
May	0.165	0.000	***	0.035	0.000	***
Jun	0.176	0.000	***	0.038	0.000	***
Jul	0.123	0.000	***	0.026	0.000	***
Aug	0.162	0.000	***	0.035	0.000	***
Sept	0.134	0.000	***	0.029	0.000	***
Oct	0.145	0.000	***	0.032	0.000	***
Nov	0.122	0.000	***	0.027	0.000	***
Dec	−0.016	0.035	*	−0.004	0.021	*
Hour (ref = 6am)						
7am	0.451	0.000	***	0.099	0.000	***
8am	0.676	0.000	***	0.148	0.000	***
9am	0.264	0.000	***	0.056	0.000	***
10am	−0.013	0.202		−0.001	0.592	
11am	−0.027	0.008	**	−0.006	0.008	**
12 pm	−0.005	0.602		0.000	0.930	
1 pm	−0.032	0.001	**	−0.006	0.020	*
2 pm	−0.047	0.000	***	−0.009	0.000	***
3 pm	0.022	0.028	*	0.006	0.017	*
4 pm	0.288	0.000	***	0.066	0.000	***
5 pm	0.586	0.000	***	0.135	0.000	***
6 pm	0.301	0.000	***	0.070	0.000	***
7 pm	0.030	0.003	**	0.007	0.002	**
8 pm	−0.091	0.000	***	−0.019	0.000	***
9 pm	−0.162	0.000	***	−0.035	0.000	***
10 pm	−0.236	0.000	***	−0.051	0.000	***
Interactions (ref = Nothing on road)						
Rain:Bus corridor	0.011	0.504		0.002	0.614	
Rain: Calmn/low traffic	0.015	0.346		0.005	0.196	
Rain: Demarcation	0.004	0.816		0.002	0.544	
Rain: Segregated	−0.023	0.140		−0.003	0.370	
Rain: Shared off road	−0.088	0.000	***	−0.027	0.000	***
Rain: Signed on road	0.009	0.568		0.001	0.813	
Adjusted R-squared	0.49109			0.46467		
F-statistic:	802.149			721.642		

Significant at the 0.10 level of significance.
* Significant at the 0.05 level of significance.
** Significant at the 0.01 level of significance.
*** Significant at the 0.001 level of significance.

CRediT authorship contribution statement

Jinhyun Hong: Conceptualization, Formal analysis, Writing - original draft. **David Philip McArthur:** Formal analysis, Writing - review & editing. **Joanna L. Stewart:** Writing - review & editing.

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Table 6
The result from a fixed-effects linear regression model with samples during the commuting time periods.

	Avg. cycling counts per infrastructure			Avg. cycling distances per infrastructure		
	Estimate	P-value		Estimate	P-value	
Weather						
Rain (rain = 1)	−0.014	0.470		−0.003	0.554	
Temperature	0.008	0.000	***	0.002	0.000	***
Day of week (ref = Sun)						
Mon	0.633	0.000	***	0.141	0.000	***
Tue	0.725	0.000	***	0.162	0.000	***
Wed	0.693	0.000	***	0.155	0.000	***
Thu	0.654	0.000	***	0.146	0.000	***
Fri	0.532	0.000	***	0.119	0.000	***
Sat	0.022	0.039	*	0.005	0.060	.
Month (ref = Jan)						
Feb	0.056	0.000	***	0.012	0.000	***
Mar	0.147	0.000	***	0.032	0.000	***
Apr	0.200	0.000	***	0.043	0.000	***
May	0.243	0.000	***	0.051	0.000	***
Jun	0.288	0.000	***	0.062	0.000	***
Jul	0.207	0.000	***	0.043	0.000	***
Aug	0.290	0.000	***	0.063	0.000	***
Sept	0.259	0.000	***	0.056	0.000	***
Oct	0.270	0.000	***	0.060	0.000	***
Nov	0.217	0.000	***	0.048	0.000	***
Dec	−0.032	0.016	*	−0.008	0.007	**
Hour (ref = 7am)						
8am	0.216	0.000	***	0.047	0.000	***
9am	−0.180	0.000	***	−0.041	0.000	***
4 pm	−0.160	0.000	***	−0.033	0.000	***
5 pm	0.128	0.000	***	0.033	0.000	***
6 pm	−0.145	0.000	***	−0.029	0.000	***
Interactions (ref = Nothing on road)						
Rain:Bus corridor	−0.022	0.425		−0.006	0.370	
Rain: Calmn/low traffic	−0.016	0.563		−0.002	0.800	
Rain: Demarcation	−0.034	0.219		−0.005	0.431	
Rain: Segregated	−0.053	0.056	.	−0.008	0.237	
Rain: Shared off road	−0.168	0.000	***	−0.046	0.000	***
Rain: Signed on road	−0.056	0.044	*	−0.014	0.034	*
Adjusted R-squared	0.565			0.537		
F-statistic:	520.730			466.350		

Significant at the 0.10 level of significance.
* Significant at the 0.05 level of significance.
** Significant at the 0.01 level of significance.
*** Significant at the 0.001 level of significance.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2020.01.008.

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