Investigating the rates and impacts of near misses and related incidents among UK cyclists

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Investigating the rates and impacts of near misses and related incidents among UK cyclists

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ABSTRACT

The paper investigates the occurrence of non-injury incidents among cyclists in the UK, seeking to (i) generate a rate that can be compared with injury rates, (ii) analyse factors affecting incident rates, and (iii) analyse factors affecting the impact of incidents on cyclists.

We collected data on non-injury cycling 'incidents' (near misses and other frightening and/or annoying incidents) from 1692 online diaries of cycle trip stages[1] and incidents, participants having signed up in advance for a specific day. Following data cleaning and coding, a dataset was created covering 1532 diary days and 3994 records of incidents occurring within the UK. Incident rates were calculated and compared to injury risks for cyclists. Cross-tabulation and regression were used to identify factors affecting incident rates and the effect an incident has on the cyclist.

Frightening or annoying non-injury incidents, unlike slight injuries, are an everyday experience for most people cycling in the UK. For regular cyclists 'very scary' incidents (rated as 3 on a 0–3 scale) are on average a weekly experience, with deliberate aggression experienced monthly. Per mile, non-injury incidents were more frequent for people making shorter and slower trips. People aged over 55 were at lower risk, as were those cycling at the weekend and outside the morning peak. Incidents that involved motor vehicles, especially those involving larger vehicles, were more frightening than those that did not.

Near miss and other non-injury incidents are widespread in the UK and may have a substantial impact on cycling experience and uptake. Policy and research should initially target the most frightening types of incident, such as very close passes and incidents involving large vehicles. Further attention needs to be paid to the experiences of groups under-represented among cyclists, such as women making shorter trips.

1. Introduction

Cyclists have a higher risk of death or serious injury, per mile, than users of motorised modes of transport except motorcycles (DfT, 2014). Despite higher mode-specific risks, public health researchers argue this is outweighed by societal health benefits (De Hartog et al., 2010). For an individual this depends on age, gender and background injury risk levels (Woodcock et al., 2009): for example, cycling risks in the UK are substantially higher than in countries such as the Netherlands (Mindell et al., 2012).

While it is government policy within UK member countries to support and increase cycling, at a national level cycling levels have barely changed. Perceived risk is a major barrier to uptake (Horton, 2007) and experiencing or even witnessing non-injury incidents may contribute. A study in the San Francisco Bay Area (Sanders, 2015) found 86% of those who cycled at least annually had experienced a near miss, with 20% having been hit. Near misses were more strongly associated than collisions with perceived traffic risk. Earlier research in Oxford, UK, by Joshi et al. (2001) highlighted near misses as a relatively common experience for cyclists.

Hence initial evidence suggests non-injury incidents may both be frequent and contribute to perceived safety, with potential impacts on uptake. However, both Sanders (2015) and Joshi et al. (2001) only examine one locality, and only Joshi et al.'s methods allow for a rate

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[1] A cycle trip stage being a part of a trip made by cycle; for example, cycling to the train station.

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calculation. This paper reports on the first national cycling 'near miss' research, providing an in-depth window into frequency and experiences. We view this as valuable given (a) over-representation of cyclists in casualty statistics, (b) government policy to increase cycling and (c) continued policy marginalisation of cycling (Aldred, 2012, 2013).

Although injury figures are high by European standards (Mindell et al., 2012; Wardlaw, 2014) a regular UK commuting cyclist is extremely unlikely to experience death or serious injury. Even a slight injury might only happen once every two decades. However, our data suggest that the 'very scary' incident is a 'normal' weekly experience, and harassment a monthly experience. This reflects the low status cyclists still have in the UK, embodied in poor cycling infrastructure design, lack of legal protection and enforcement, and low empathy from other road users (Aldred, 2012, 2013). Similar issues are likely to arise in other low-cycling countries where cycling's status is low (see e.g. Daley and Rissel, 2011). All these factors are likely to counteract policy aims to increase cycling.

2. Material and methods

The study asked participants to complete an online diary, using KeySurvey software. Ethical approval was granted by the University of Westminster. A convenience sample of people who cycle was recruited with channels including organisational mailing lists, cycling organisations, some leafleting (in London), social media dissemination, and previous survey participants who had agreed to be re-contacted. As registration was open and online, while the survey was aimed at people cycling in the UK, a small number of people from other countries did also complete it.

Participants registered online and nominated a day over a two-week period to record trips and any incidents. This provided some advantages over other methods used to examine near-misses, by allowing us to calculate a rate per trip stage, hour or mile travelled. By contrast, the various apps and reporting systems[2] offering posthoc reporting do not allow the calculation of rates.

The survey questionnaire included a range of quantitative and qualitative questions, with the focus here being the former. Cyclists were asked to record the cycle trips they made, when each started and finished, and distance travelled. They also provided some basic demographic and residential location data. The number of incidents (defined as causing some level of annoyance and/or fear) experienced while cycling on their diary day was recorded. This was left open to enable participants to self-define incidents, with coding later taking place to allocate descriptions to inductively generated categories. To minimise respondent burden, participants were only asked for the details of the first 10 incidents. For each, people were asked for the location, a description, details about other road users' involvement, its effect on them (immediately and any likely impact in the future), and whether and how the incident might have been prevented.

The survey produced 1692 completed day diaries, with the number of individual participants slightly lower as several completed two diaries. Around 60% of participants who initially registered fully completed the diary. People were encouraged to complete the diary whether they had no, few, or many incidents; however, possible bias might run both ways. Those experiencing no incidents may not have bothered to complete it, conversely, so may those experiencing many incidents and finding the diary too onerous.

Participants commented that they might not have noticed many recorded incidents, had this not been their 'diary day'. This could be interpreted as bias in the sense that we were eliciting incidents that normally would not have mattered to people. However, we would argue that the survey gives voice to incidents that would otherwise count for nothing. The qualitative material collected in this study, like other research (see e.g. Pooley et al., 2013), suggests that to cycle regularly in an often difficult context, people must develop a level of tolerance for unpleasantness and hostility. Hence, in asking people about any annoying or frightening incidents, the study has brought to the fore events which – despite having some level of negative consequence, even if only mild annoyance – might otherwise have been accepted as part of their cycling experience.

The study has other limitations. Without GPS tracking, it does not allow the calculation of risks by infrastructure type as we lack information on whole route characteristics. We piloted the concomitant use of an app; however, the diary alone required substantial commitment and we believed using both would have lowered response rates significantly. Another limitation is the focus on the 'cyclist's perspective', unlike Joshi et al. (2001). However, we feel this is justified within a small project because of the strong policy relevance of investigating cycling near misses, and because it allows us to explore how cyclists themselves define near miss and related incidents.

Analysis was conducted using SPSS, Excel, and NVivo. This involved various stages, including cleaning and coding data (e.g. coding incident categories, cross-checking reported involvement of others, etc.). Non-UK incidents were removed, as were several hundred incidents classed as either reported in error or as, for example, witnessed rather than directly experienced. This produced a dataset containing 4662 incidents. 96.7% (1596) of those participants experienced between 0 and 10 incidents (84.9% experienced 0–5 incidents). We removed the 55 people (3.1%) who recorded over 10 incidents (maximum = 55) as outliers. The justification for this was that (a) these people may have been using a different definition of incident compared to others and (b) incident data were for them by definition incomplete as we only obtained information on the first 10 incidents. Nine more participants were removed due to incomplete time or distance data. Hence the following analysis relates to 1532 UK-based diarists and 3994 incidents.

3. Results

3.1. Demographics

Participants were disproportionately male (72.1%). This broadly reflects the gender balance of UK cycling with the English National Travel Survey[3] showing that men make three times more cycle trips than women (22 per year compared to 7 per year). The age distribution was also skewed, with a relatively low proportion of under-25s. The decline at older ages is characteristic of utility cycling in countries such as the UK (Pucher and Buehler 2008) (Fig. 1).

[2] For example Collideoscope or the CTC's Road Justice project for reporting bad driving.

[3] https://www.gov.uk/government/statistical-data-sets/nts06-age-gender-and-modal-breakdown.

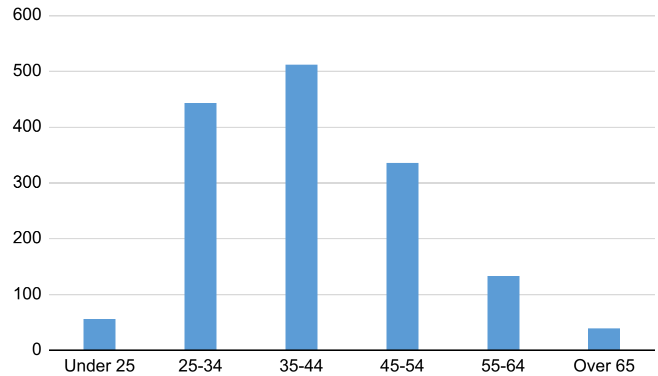

Fig. 1. Age distribution of diarists (n=1519/1532).

Most diarists lived in England or Scotland, with the largest group (32.1%) living in London. This is less representative but reflects the high profile of cycling in London and us having publicised the survey to a greater extent there. 92.2% of diarists were travelling during the week, with the remainder making generally longer, leisure-focused weekend trips. 68.3% of diarists recorded trips during 'Week One' (20th–26th October 2014) and 31.7% in 'Week 2' (27th Oct–2nd November). Differences by week could have been significant for two reasons. Firstly, British Summer Time ended at the end of the first week, meaning lighter mornings and darker evenings. Secondly, in England the second week was half-term holiday for many schools, leading to lower levels of motor traffic on the roads.

3.2. Incident rates

3.2.1. Summary statistics and comparison with injuries

Table 1 provides summary statistics at diary day level about numbers of incidents, time, speed and distance, for those experiencing 10 or fewer incidents. Both distance (median=12.0 miles) and time spent cycling (median=70.0 min) are positively skewed by a minority of longer, mostly leisure-focused trips.

Dividing number of incidents by total distance (or time) generates a rate of .172 incidents per mile (or 1.82 incidents per hour), similar to the per-mile rate for cyclists in Joshi et al. (2001), although our participants in general report travelling further and faster than Joshi's. Calculating individual rates, and then taking the mean of these, provides a different and higher rate: .293 incidents per mile and 2.41 incidents per hour cycled. This latter calculation indicates a discrepancy in incident experience by distance travelled (which is correlated with speed) which will be discussed later. Across the sample, looking at incidents per hour cycled, 75% of participants experienced at least .75 incidents per cycled hour, with a median of 1.71 per hour. So rather than an occasional occurrence, non-injury incidents are an everyday experience for most UK cyclists.

Combined with other information on injury risk, the research allows us to draw conclusions about the relative frequency of injury and non-injury incidents. Within England in 2011, the road injury statistics recorded 32 cyclist deaths and 1015 serious injuries per billion miles cycled; in London these rates are 44 deaths and 1542 serious injuries per billion miles cycled (Keep, 2013). Slight casualty rates reported in Britain are around 6 times greater than KSI figures (killed or seriously injured; Department for Transport, 2013), although these (and to a lesser extent serious injuries) are substantially under-reported. The Münster Bicycle Study found police records only contained half the injuries recorded in hospital records (Juhra et al., 2012). Self-report studies find injury numbers to be at least three times greater than those contained in either hospital or police records (Tin Tin et al., 2013).

Thus in the UK, reported deaths, serious injuries, slight injuries, and self-report injuries might be of the rough magnitude of around 50; 1000; 6000; and 20,000 per billion miles cycled respectively. This research suggests that, per billion miles cycled, one might by contrast expect 25,000,000 'very scary' near miss incidents – a completely different metric and one that can contribute to our understanding of why people apparently over-estimate the risks of cycling. Table 2 presents for the comparison a regular commuting cyclist riding 2500 miles per year (i.e. approximate commuting distance of 5 miles each way).[4]

3.2.2. Incidents and exposure by time of day

Collecting trip timing data has enabled us to analyse incidents and exposure by time of day. Many trips in our sample represented journeys to work. The graph below shows the classic 'a.m.' and 'p.m.' peaks also found for other modes of transport, although particularly strong for cycling (Fig. 2).

Incidents were categorised by hour of day, and mapping these onto exposure shows incident rate per hour, for each hour of the day (Fig. 3). With numbers of trips and incidents extremely low between midnight and 5 a.m., we have only included in Fig. 3 trips and incidents taking place outside those hours. The incident rate throughout the day changes roughly in line with the time distribution graph, also illustrating a.m. and p.m. peaks.

We then plotted the hourly incident rate figure against the cycling levels found in our dataset; seeing the latter as a proxy for broader cycling rates where our participants live and ride. There is a strong and positive correlation. Fig. 4 shows the relationship between hourly incident rate and hourly cycling volume for each hour of the day (for example, the right-hand data point shows that between 8 and 9 a.m., both cycling volume and hourly incident rate are highest).

Finally, we considered the impact of light and darkness. This is complex because lighting levels vary by area and by weather condition; however, as an approximation we assumed that during Week 1 8 a.m. to 6 p.m. represented daylight while in Week 2, after the clock

[4] This is used to compare metrics and does not represent a specific average.

Table 1
Incidents, minutes cycling, speed, distance (10 or fewer incidents, 1532 diarists).

	Minimum	Maximum	Sum	Mean	Median	Std. deviation
Incidents	0	10	3994	2.61	2.0	2.19
Time (min)	10	515	131,983	86.15	70.0	58.09
Distance (miles)	.20	122.0	23,267	15.12	12.0	12.55
Speed (mph)	.6	33.8	–	10.27	10.0	3.86

Table 2
Approximate incident rate comparison, regular commuting cyclist.

Type of incident	Rate per year, regular UK commuting cyclist	Explanation of rate calculation
Death	.000125	First three rates derived from reported cycle injury rates for England, assuming a regular cyclist rides 2500 miles per year; so dividing the rate per billion miles above by 400,000.
Reported serious injury	.0025	
Reported slight injury	.015	
Any injury (reported or not)	.05	Self-report injury rate derived from Tin Tin et al.'s factor of three compared to reported injuries.
Harassed/abused by other road user	20	23,267 diary miles were associated with 193 deliberate incidents, 569 'very scary' incidents and 3994 incidents in total. Assuming a regular cyclist rides 2500 miles per year, dividing by nine gives an approximate annual rate.
'Very scary' incident	60	
Any near miss/non-injury incident	450	

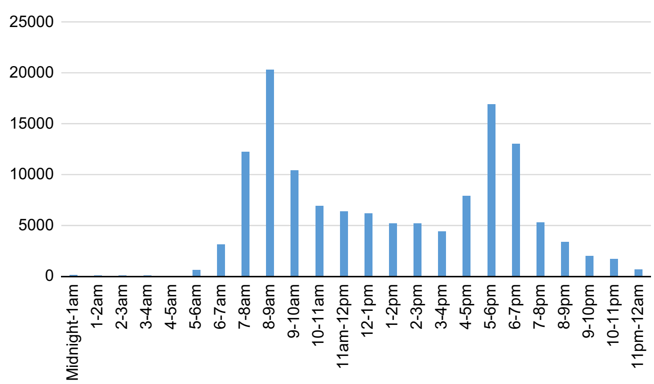

Fig. 2. Minutes cycled in each one hour time bin.

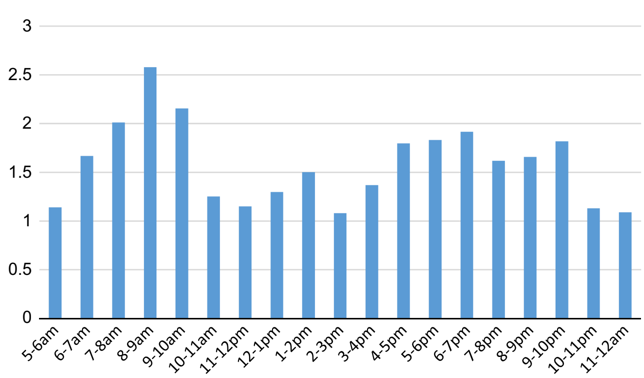

Fig. 3. Average incident rate per hour, in one hour time bins, 5–12 a.m.

change, daylight hours would be 7 a.m. to 5 p.m. Weekend trips were excluded for this specific analysis.[5] Relatively little difference by light condition (2.03 incidents per hour in daylight across both weeks, vs. 1.81 incidents per hour after dark) was found.

3.3. *Factors affecting incident rates*

t-Tests were conducted to discover whether incident rate per hour and per mile cycled differed significantly ($p < .05$) by various person-level variables.

[5] These tended to be leisure trips thus more likely to take place entirely during daytime hours, unlike utility trips.

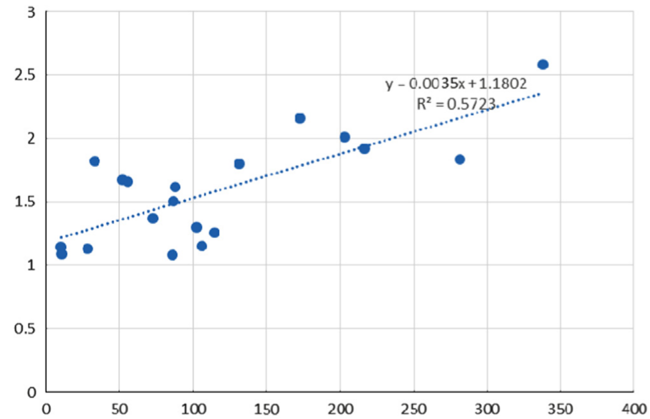

Fig. 4. Scatterplot, hourly cycling volumes vs. hourly incident rate (5–12 a.m. only).

3.3.1. Gender

Women had a higher incident rate per hour than men; 2.78 vs. 2.27 ($p < .05$). Rates per mile were even further apart, with the women's rate around twice the men's; .423 vs. .240. This relates to statistically significant gender differences in travel characteristics: women reported a mean distance travelled of 11.5 miles on their diary day (mean speed 8.4 miles per hour, mean time spent cycling 80.0 min) against 16.7 miles for men (speed 11.0, time 89.4 min). When comparing incidents per cycle trip stage, there was no significant difference between men and women. While our sample is not random, we might expect to see gender differences in distances and speeds within the wider cycling population. British National Travel Survey data show women's cycle trips are generally shorter in distance than men's,[6] while De Geus et al. (2014) found Belgian cycling speeds similarly varied by gender (19.5 km h vs. 15.5 km h).

When examining categories of incident (discussed more fully under Section 3.4), we also investigated women's reporting of problematic (generally too close) passes – one of the more common and more frightening types of near miss. We found that differences in rates per trip stage or per hour were not statistically significant, while differences per mile were, with women reporting 50% more passing incidents than men, per mile cycled (Table 3).

3.3.2. Other factors

A large difference (also significant at the 95% level) was found comparing weekday to weekend cycling. Those cycling at the weekend experienced 1.39 incidents per hour, against 2.60 for weekday cyclists; per mile, rates were .14 vs. .32. Weekend cyclists were on average cycling for much longer than weekday cyclists (151.4 vs. 81.3 min), as might be expected if most weekend travel was for leisure purposes. Accordingly the incident rate per cycle trip stage was actually higher for weekend cyclists (Table 4).

Incident rates did not differ significantly depending on the week, with neither hourly, per mile, or trip stage rates being significant at the $p < .05$ level. Similarly, we found no effect related to whether or not a person lived in London for any of the three indicators.

A statistically significant difference was found between the rates of the three indicators when comparing under- and over-55s, but the different age cohorts in the under-55 range were relatively similar, albeit with a peak of 2.83 incidents per hour for 25–34 year olds (Table 5).

3.3.3. Regression analysis

To control for confounding, a regression model was fitted. A log transformation of incidents per hour created a near-normal distribution. Because this removes the 15% with no incidents, we investigated the characteristics of that group separately. Individual cross-tabulations of the no-incidents subgroup showed no significant difference from others by gender, living in London, week of diary, or weekday vs. weekend. Those aged over 55 were more likely to report zero incidents (20.9% of this age group, against 14.3% for people aged 55 and under).

Time cycling and number of trip stages did not differ significantly. *t*-Tests found small but statistically significant ($p < .05$) differences in trip characteristics; the no-incidents group having lower distances and speeds. However, these differences only seemed to hold true for men, whereas women experiencing no incidents were similar in all trip characteristics to other women (Table 6).

Explanations for why around 15% of participants experienced no incidents might include differences in behaviour (by cyclists and/or drivers), infrastructure, and incident tolerance. Many free text comments left by these participants highlighted infrastructure, for example, some stating that their route on their diary day was mostly away from motor traffic. Unfortunately without route data we lack a measure of route separation from motor traffic, and thus route characteristics represent the major missing variable in the analysis. Others said that they thought they had had fewer incidents because their ride was shorter than usual, because of the weather, or because of the half-term holiday. It is also possible that some of the no-incidents group are using a different definition of incidents, with a few mentioning pot-holes or close passes in free text comments but without actually recording any incidents.

Having excluded the 'no-incident' group, a linear regression model was run with the dependent variable being the natural log of incident rate per hour. Predictors included were

a) exposure in each hour bracket,
b) proportion of time spent cycling in the morning peak (7–10 a.m.),

[6] Calculated from NTS 2013 data tables NTS0601 and NTS0605, available at https://www.gov.uk/government/statistics/national-travel-survey-2013.

Table 3
Problematic passing incidents and gender (male $N=1101$; female $N=425$).

	Gender	Mean
Problematic passes per hour cycled	Male	.65
	Female	.70
Problematic passes per mile cycled	Male	.066
	Female	.099
Problematic passes per trip stage	Male	.39
	Female	.33

Table 4
Weekday vs. weekend incident rates (weekday $N=1412$; weekend $N=120$).

		Mean
Incidents per hour cycled	Weekday	2.504
	Weekend	1.350
Incidents per mile	Weekday	.307
	Weekend	.136
Incidents per cycle trip stage	Weekday	1.209
	Weekend	1.713

Table 5
Age-related differences (55 and younger $N=1347$; over-55 $N=172$).

Respondent 55+		Mean
Incidents per hour cycled	55 and younger	2.514
	Over-55	1.546
Incidents per mile	55 and younger	.299
	Over-55	.196
Incidents per cycle trip stage	55 and younger	1.274
	Over-55	1.045

Table 6
Distance and speed differences, no-incident vs. incident group, and by gender.

Both genders		*N*	Mean
Distance (miles)	No incidents	230	13.67
	Incidents	1302	15.46
Speed (mph)	No incidents	230	9.69
	Incidents	1302	10.37
Men			
Distance (miles)	No incidents	176	14.40
	Incidents	925	17.09
Speed (mph)	No incidents	176	10.21
	Incidents	925	11.16
Women			
Distance (miles)	No incidents	54	11.28
	Incidents	371	11.52
Speed (mph)	No incidents	54	7.99
	Incidents	371	8.46

c) proportion of time spent cycling in the evening peak (4–7 p.m.),
d) speed,
e) gender,
f) being over 55,
g) living in London,
h) weekday or weekend,
i) diary week (1 or 2).

This model achieved an adjusted R-square of .333 (see Appendix for full model output). Individual significant ($p < .05$) coefficients were weekend (lower rates), respondent over 55 (lower rates), proportion of time spent cycling in the morning peak (higher rates), and time spent cycling during 14 individual time slots (lower rates). Gender was not significant, suggesting that underlying women's higher incident rates is a broader association between shorter, slower trips and higher incident rates.

To further explore relationships between distance, time, speed and incidents, a similar regression model was run but using logged incidents per mile as the dependent variable. This achieved an adjusted R-square of .477, with speed strongly predicting incident rate per mile (standardised coefficient of $-.404$). Hence, for a given journey length, faster cyclists experienced relatively fewer incidents. The unstandardised coefficient for speed was −.101; meaning a one mile per hour increase in speed is associated with a 9.6% decrease ($e^{-.101}-1$) in incident rate per cycled mile. Fig. 5 illustrates this association between speed and incident rate per mile, using cross tabulated data.

3.4. Factors affecting incident impact

3.4.1. Type of incident

While incidents were common they differed substantially. Respondents were asked to rate incidents on a 0–3 scale for how 'scary' and 'annoying' they were, and this section explores these incident characteristics further. The first table explores the distribution of more and less scary and annoying incidents among participants. Of all 1532 participants, just over half experienced one or more very annoying and/or very scary incident/s on their diary day. Around one in four (24.0%) experienced a very scary incident, with around half (50.5%) experiencing a very annoying incident (Table 7).

In 85.2% of cases, other road users were involved, and 70.0% of incidents involved motor vehicles. Incidents tended to have similar characteristics and were allocated to eight categories. The most common was blocking, followed closely by a problematic pass (Table 8).

3.5% of incidents were judged 'not annoying' (0 on the 0–3 scale), and 25.5% 'not scary'. Overall, 41.3% of incidents were 'very annoying' and 14.4% 'very scary'. In other words, even incidents that have a more extreme impact on the respondent are relatively common.

We examined factors associated with the more extreme reactions, and found that incidents involving any kind of motor vehicles were significantly more scary (18.1% vs. 5.7% 'very scary') and annoying (44.3% vs. 34.4% 'very annoying') than those not. Incidents involving large vehicles were particularly frightening, with 24.0% of incidents involving HGVs and 22.8% of incidents involving buses or coaches being judged as 'very scary'. Being blocked – in many cases not involving any moving vehicles – was less likely to generate fear than other incident types. For example, while almost one in four dooring, hooking, and passing incidents were judged 'very scary', only 6.2% of blocking incidents were categorised in this way. The underlined figures in Table 9 indicate where an incident type is particularly likely

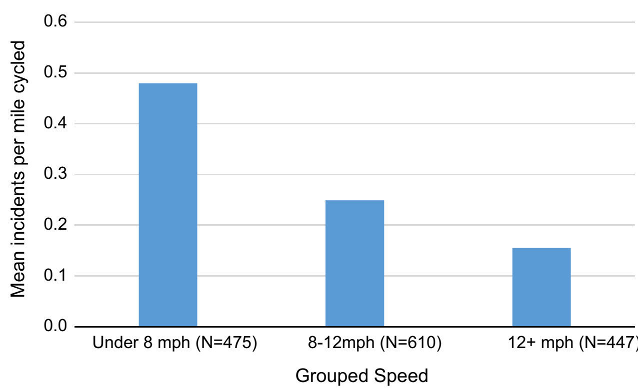

Fig. 5. Variation in mean incident rates by grouped speed.

Table 7
Experience of very scary and very annoying incidents (person-level).

			Very annoying incident/s?		Total
			No	Yes	
Very scary incident/s?	No	Count	716	449	1165
		% of total	46.7	29.3	76.0
	Yes	Count	43	324	367
		% of total	2.8	21.1	24.0
Total		Count	759	773	1532
		% of total	49.5	50.5	100.0

Table 8
Incident categorisation.

Description	Frequency	Per cent
Cyclist's way blocked (by other road users, road conditions, etc.)	1506	37.7
Problematic pass manoeuvre (usually too close)	1169	29.3
Vehicle pulls out or in across cyclist's path	644	16.1
Person drove (or cycled) at cyclist head on	255	6.4
Near left or right hook (road user turns across cyclist's path)	215	5.4
Other type of incident	107	2.7
Tailgating cyclist, but does not/cannot pass	72	1.8
Person opened car door in cyclist's way	26	.7
All incidents	3994	100

Table 9
Incident categories and 'very scary' or 'very annoying' ratings.

Incident type		All categorised incidents	Of which very scary	Of which very annoying
1. Cyclist's way blocked	Count	1479	91	538
	% within category		6.2	35.8
2. Problematic pass (usually too close)	Count	1159	255	550
	% within category		22.0	47.5
3. Other vehicle pulls in or out	Count	641	105	274
	% within category		16.4	42.6
4. Being driven (occasionally cycled) at	Count	254	44	112
	% within category		17.3	44.3
5. Left or right hook incident	Count	214	47	98
	% within category		22.0	45.6
6. Other type of incident	Count	106	8	36
	% within category		7.5	33.6
7. Other vehicle tailgates cyclist	Count	72	13	25
	% within category		18.1	34.7
8. Dooring incident	Count	26	6	10
	% within category		23.1	38.5
All incidents	Count	3951	569	1643
	% within category		14.4	41.3

Table 10
Proportion of incidents judged deliberate, weekday and weekend.

			No deliberate incidents	One or more deliberate incident/s	Total
	Weekday	Count	1316	95	1411
		% within weekday	93.3	6.7	100.0
	Weekend	Count	105	15	120
		% within weekend	87.5	12.5	100.0
Total		Count	1421	110	1531
		% within all	92.8	7.2	100.0

Table 11
Deliberate incidents and level of scariness/annoyingness.

		N	Mean
How annoying	Not deliberate	3789	2.10
	Deliberate	190	2.48
How scary	Not deliberate	3759	1.28
	Deliberate	192	1.47

(more so than for incidents in general) to be judged as 'very scary' or 'very annoying' (excluding 43 incidents where annoyingness and/or scariness were not rated).

3.4.2. Deliberate incidents

4.8% of incidents ($N=193$) were judged to involve deliberate harassment or aggression (such as verbal abuse, or revving and beeping); 110 participants reported one or more such incident. Despite the low numbers, we did find a statistically significant ($p<.05$) difference between those whose diary day was during the week compared with those making journeys at the weekend as to whether or not they experienced a deliberate incident; deliberate incidents affected a bigger proportion of trips at the weekend. By contrast, there were no statistically significant differences by gender, being over 55, living in London, or diary week (Table 10).

Comparing incidents categorised as deliberate with those categorised as not deliberate, a pattern emerges (although numbers are small in some categories). Deliberate incidents are particularly likely to be passing and/or tailgating incidents; over half falling in one of these two categories (often referred to as a 'punishment pass'). One fifth of deliberate incidents are categorised as 'other', and these tend to be 'pure' harassment (rather than aggressively conducted manoeuvres), including in one case racial abuse from a driver.

Deliberate incidents were also significantly more likely to be rated as more annoying and more frightening than non-deliberate incidents. Table 11 compares annoyance and scariness ratings (using the 0–3 scale) for both deliberate and non-deliberate incidents.

3.4.3. Regression analysis

Again a linear regression model was estimated to control for confounding. This used 'how scary' as the dependent variable, with independent variables including gender, whether the incident took place during one of the morning (7–10 a.m.) or evening (4–7 p.m.) peak hours, whether it took place in London, whether the cyclist was over 55, weekday or weekend, diary Week 1 or 2, involvement of specific other types of road user (e.g. car, cyclist), type of incident (using dummy variables, with BLOCK as default), and whether an incident was judged deliberate. The adjusted R-square was .163 (see Appendix for full model output).

In the regression model, significant variables ($p<.05$) associated with an incident being more scary were incident time between 6 and 7 p.m., weekend, greater cycling speed, involvement of cars, vans, buses/coaches, HGVs or 'other vehicles', and the incident being any type other than ‘block’ or ‘other’. By contrast the involvement of pedestrians or other cyclists was associated with an incident being less scary ($p < .05$). The largest standardised coefficient (a way of assessing which variable has the largest contribution to incident scariness) was for a ‘passing’ incident, followed by pulling out, hook, and ‘driving at’ incidents, then involvement of HGVs and buses/coaches. Experiencing a passing rather than a blocking incident, for example, is associated with an increase of .697 in the scariness rating (based on the unstandardised coefficient). The involvement of HGVs is associated with an increase in scariness rating of .412, compared to an incident not involving HGVs.

The positive weekend coefficient suggests that while weekend riders had a lower rate of incidents overall, a relatively high proportion was frightening. Potentially this might be because weekend riders travelling longer distances may be using rural A-roads and experiencing close passes at higher speeds. While speed was associated with increased scariness of incidents, this was a very small effect, with an unstandardised coefficient of .009.

4. Discussion

4.1. The ‘Normality’ of near misses

The headline finding of this paper is that, in the UK, near misses seem to be ‘everyday’ occurrences, with the vast majority of our sample experiencing at least one on their diary day. One in four experienced an incident that they rated as being ‘very scary’. Despite government aims to promote cycling, attitudes of other road users towards cyclists remain negative and it is possible that this contributes to a startlingly high risk of near miss incidents (Christmas and Helman, 2011).

Few cyclists seem to be able to avoid such incidents. While around one in seven experienced none on their diary day, some of these specifically said that they would normally expect incidents to happen. Interestingly there only seemed to be small differences by diary week, while a number of ‘second week’ diarists had hypothesised that this data would be unusable because the English school holiday meant that very few incidents would be experienced. Perhaps the lower numbers of motor vehicles on the roads was compensated by the higher speeds of those remaining.

Similarly there was no peak in rates during the hours of darkness; if anything, rates seemed slightly lower, even though it is widely agreed that KSI (being killed or seriously injured) risk on the roads is substantially higher during the hours of darkness (Johansson et al., 2009). One possible factor in this discrepancy, given the differences we found for weekday vs. weekend cycling, might be that leisure riding is much more likely to take place during daylight. It may also be true that (a) the risks of near misses differ from KSI risk in this respect, and (b) cyclists are more likely to notice near misses during daylight hours (which in itself might have a protective effect in relation to more serious outcomes).

4.2. Incident rates

A strong negative association between cycling speeds and incident rates per mile was apparent when comparing group means, remaining as a strong predictor variable in regression analysis. This suggests that those unable to keep up with motor traffic may have substantially more near miss experiences on a given journey. Another explanation, given we are talking about overall journey speeds, might be that cyclists jumping red lights might be simultaneously (a) speeding up their journey and (b) reducing near miss risk by reducing interaction with motor vehicles. We do not know, but as avoiding conflict with motor traffic is a reason sometimes given by cyclists themselves for red light jumping, this pathway is also plausible. One other explanation could be that less ‘hardy’ cyclists are particularly sensitive to near misses. Whatever the reason/s, the finding is worrying.

The incident rate data also contribute to debates over ‘safety in numbers’ (Jacobsen, 2003), which so far has been discussed in relation to injuries rather than near misses. One might invoke a number of pathways to explain why where there is more cycling, there tends to be safer cycling. For example, where cycling is safer, this might encourage more cycling. Conversely, causation might be the other way round, and two potential explanations are that (a) where cycling is, or becomes, higher, more people know a cyclist personally and so it becomes more culturally acceptable, hence motorists treat cyclists better on the roads, or (b) where there are higher numbers of cyclists on key routes, the sheer volume of people riding provides some protection from injury (Thompson et al., 2015).

Interestingly, explanation (a) seems to have a direct link with near misses, in that one might also expect the cycling experience to involve fewer unpleasant incidents/conflicts as cycling becomes more accepted. Explanation (b) might have an indirect link with near misses if there is some correlation between near misses and injury risk, even if not an exact one. Either way, this paper fails to provide clear evidence of a safety in numbers effect. Incidents happen to London residents at similar rates to those who live outside London, despite cycling's high political prominence in the capital. Similarly the incident rate per hour cycled in the morning peak seems relatively high, despite this being a time when large numbers of cyclists are on the roads in some cities: in London now, bicycles form a quarter of traffic on key commuter routes in the morning peak (GLA, 2013). While this does not in itself ‘disprove’ the safety in numbers thesis, it suggests that one should be cautious about assuming this relationship will automatically hold in contexts such as the UK, where hostility towards cyclists remains much more prevalent than in high-cycling, high-safety countries such as The Netherlands and Denmark.

Another sobering result is the relatively high incident rate reported by women, which regression analysis suggested was a result of their lower speeds and shorter trips, both likely to be gender differences characteristic of broader cycling populations. Given Sanders' (2015) findings about the off-putting nature of near misses, this gender difference may be a factor in women's lower cycling rates. It contradicts one commonly held view: that female cyclists are treated better on the roads than male cyclists, because they are assumed to be less experienced and hence less predictable (Walker, 2007; Love et al., 2012; but see also Walker et al. (2014) for conflicting data). These data suggest otherwise. When looking at problematic (usually close) passes, women report 50% higher rates than men per mile cycled (with no difference per hour, or per cycle trip). This is at odds with the conclusion in Walker (2007) that women cyclists are given greater passing space than are men. Walker's research was based on him wearing a blond wig for some trips during his study of passing distances, while this finding is based on comparing women's and men's reported experiences. Explanations could include: that (a) contrary to his belief, drivers did not assume Walker in a blond wig was female, or (b) that women are less tolerant of motor vehicle proximity than are men.

Our findings in relation to gender and near misses contrast with those of Hollingworth et al. (in press) who found women less likely than men to report having experienced a cycling injury in the last five years. By contrast, we consistently found a lower rate of reported near misses for over-55s, similar to Hollingworth et al.'s finding of lower injury risk for the over-60s. This relatively reduced risk at older ages seems unusual given older people's greater vulnerability to injury, which leads to the higher risk for older people cycling in The Netherlands where cycling at all ages is common (Mindell et al., 2012). One explanation might be that in low-cycling contexts, those older people who continue to cycle are an extremely fit and skilled minority; and their cycling is also more likely to be weekend long-distance leisure riding, which in our study appears to be lower risk than utility cycling.

One other interesting finding in relation to rates is that the only variable associated with a greater likelihood of an incident being deliberate was weekend cycling. While weekend cycling was generally lower risk, incidents were both (a) relatively likely to be very scary and (b) relatively likely to be deliberate. This might be explained by a thesis advanced in Aldred and Jungnickel (2012): leisure riding is doubly marginalised, seen as unwelcome on UK roads not just because of being cycling, but also because of *not being transport*. There is tentative evidence to suggest that potentially such rides are in general less eventful (perhaps partly due to lower motor vehicle volumes) yet, when an incident does occur, it may be more problematic and/or hostile than the average incident experienced by a utility cyclist.

4.3. The impact of incidents

While the regression model fit looking at the scariness of incidents was lower here than for the factors affecting incident rates, patterns do exist affecting the impact of incidents. The lower *R*-squared statistic is perhaps unsurprising given evidence from the qualitative survey data showing that people characterise situations differently; for example, some more confident cyclists said they experience incidents as 'annoying' whereas others might judge them as being 'scary'.

However, the cross-tabulations and the regression model both highlighted that incidents involving motor vehicles, particularly large ones, and those that are moving (as opposed to being blocked by infrastructure or parked cars, for example) are particularly frightening. Given the higher injury risks also posed by these kinds of situations – for example, relatively high risks posed to other road users by bus, coach and heavy goods vehicles (TfL, 2012) – there are implications here for what situations to focus on both for encouraging uptake of cycling and for preventing injury to cyclists.

4.4. Future research

More research could usefully (a) delve further into the extent of a 'safety in numbers' effect in relation to near miss incidents, (b) use cross-national research to explore differences between countries, (c) collect more data in order to be able to draw stronger conclusions about deliberate incidents, (d) attempt more systematically to triangulate 'objective' and 'subjective' data and thus establish, for example, whether women experience more close passes than men per mile, or whether women and men have different definitions of what constitutes a 'close pass', and (e) explore near misses in relation to infrastructure types.

5. Conclusions

This research has highlighted the frequent experience of cycling near miss incidents in the UK, including those incidents categorised as 'very scary'. While pedestrian conflicts and near misses are increasingly studied to measure and improve walking experiences (particularly in relation to cyclists, e.g. York and Tong, 2014), cycling near misses remain 'off the radar', despite their likely contribution to 'fear of cycling' (Horton, 2007). Policy-makers should pay similar attention to causes and effects of cycling near-misses, particular incidents that are more frightening (e.g. close passes) or those more likely to lead to injuries (e.g. incidents involving large vehicles). Preventing near misses is valuable both for injury reduction (for example, designing out left hook risks—a common category of incident), but also for improving the cycling experience.

Policy currently seeks to diversify cycling, for example in relation to gender, and in this context it is concerning that women seem to experience a higher rate of near miss incidents than do men. Regression analysis suggested this was based on an association between shorter, slower trips and higher incident rates. More attention should therefore be paid to the experiences of slower and possibly less risk-tolerant cyclists. Finally, the high rates of incidents at peak times calls into question the extent to which safety in numbers might apply to near miss incidents, and this could usefully be further investigated.

Author contributions

RA designed and led the study design and analysis, and drafted the article. SC assisted with survey coding and analysis, and contributed to the article.

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Appendices

First regression model

Variables entered/removed[a].

Model	Variables entered	Variables removed	Method
1	PROPpmPEAK, SPEED, Diary week, 1–2 a.m., 8–9 a.m., 11 p.m. to 12 a.m., 56 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a.m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m. [b]		Enter

[a] Dependent variable: Log (incidents per h).
[b] All requested variables entered.

Model summary.

Model	*R*	*R* square	Adjusted *R* square	Std. error of the estimate
1	.591[a]	.349	.333	.67934

[a] Predictors: (Constant), PROPpmPEAK, SPEED, Diary week, 1–2 a.m., 8–9 a.m., 11 p.m. to 12 a.m., 5–6 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a.m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m.

ANOVA[a].

Model		Sum of squares	df	Mean square	*F*	Sig.
1	Regression	306.566	31	9.889	21.428	.000[b]
	Residual	572.267	1240	.462		
	Total	878.833	1271			

[a] Dependent variable: Log (incidents per h).
[b] Predictors: (Constant), PROPpmPEAK, SPEED, Diary week, 1–2 a.m., 8–9 a.m., 11 p.m. to 12 a.m., 5–6 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a.m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m.

Coefficients[a].

Model		Unstandardised coefficients		Standardized coefficients	*t*	Sig.
		B	Std. error	Beta		
1	(Constant)	1.240	.117		10.599	.000
	SPEED	.002	.006	.009	.359	.719
	Diary week	.015	.042	.008	.362	.717

midnight–1 a.m.	−.012	.010	−.029	−1.236	.217
1–2 a.m.	−.006	.020	−.010	−.319	.749
2–3 a.m.	.023	.053	.046	.429	.668
3–4 a.m.	−.027	.068	−.042	−.395	.693
5–6 a.m.	−.012	.005	−.057	−2.392	.017
6–7 a.m.	−.004	.003	−.044	−1.702	.089
7–8 a.m.	−.012	.002	−.211	−6.949	.000
8–9 a.m.	−.011	.002	−.214	−6.916	.000
9–10 a.m.	−.010	.002	−.174	−5.589	.000
10–11 a.m.	−.006	.002	−.093	−2.668	.008
11 a.m. to 12 p.m.	−.007	.002	−.117	−3.185	.001
12–1 p.m.	−.004	.002	−.065	−1.840	.066
1–2 p.m.	−.004	.002	−.050	−1.639	.101
2–3 p.m.	−.009	.002	−.115	−3.903	.000
3–4 p.m.	−.004	.002	−.046	−1.645	.100
4–5 p.m.	−.009	.002	−.131	−4.256	.000
5–6 p.m.	−.011	.002	−.197	−5.831	.000
6–7 p.m.	−.010	.002	−.172	−5.255	.000
7–8 p.m.	−.009	.002	−.104	−3.967	.000
8–9 p.m.	−.009	.003	−.080	−3.195	.001
9–10 p.m.	−.009	.003	−.064	−2.631	.009
10–11 p.m.	−.007	.004	−.045	−1.850	.065
11 p.m. to 12 a.m.	−.012	.006	−.051	−2.155	.031
Participant lives in London	.001	.044	.001	.024	.981
Weekend dummy variable	−.160	.084	−.051	−1.919	.055
Gender dummy variable	.057	.045	.031	1.267	.205
Respondent 55+	−.180	.067	−.066	−2.674	.008
PROPamPEAK	.385	.142	.116	2.716	.007
PROPpmPEAK	.267	.161	.078	1.652	.099

[a] Dependent variable: Log (incidents per h).

Second regression model

Variables entered/removed[a].

Model	Variables entered	Variables removed	Method
1	PROPpmPEAK, SPEED, Diary week, 1 – 2 a.m., 8 – 9 a.m., 11 p.m. to 12 a.m., 5–6 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a.m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m.[b]		Enter

[a] Dependent variable: Log (inc per mile).
[b] All requested variables entered.

Model summary.

Model	*R*	*R* square	Adjusted *R* square	Std. error of the estimate
1	.700[a]	.490	.477	.69148

[a] Predictors: (Constant), PROPpmPEAK, SPEED, Diary week, 1–2 a.m., 8–9 a.m., 11 p.m. to 12 a.m., 5–6 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a.m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m.

ANOVA[a].

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	569.937	31	18.385	38.450	.000[b]
	Residual	592.905	1240	.478		
	Total	1162.842	1271			

[a] Dependent variable: Log (inc per mile).
[b] Predictors: (Constant), PROPpmPEAK, SPEED, Diary week, 1–2 a.m., 8–9 a.m., 11 p.m. to 12 a.m., 5–6 a.m., 9–10 p.m., midnight–1 a.m., Respondent 55+, 7–8 p.m., 10–11 p.m., 3–4 p.m., 7–8 a.m., Participant lives in London, 8–9 p.m., 6–7 a.m., Gender dummy variable, 9–10 a. m., Weekend dummy variable, 1–2 p.m., 6–7 p.m., 4–5 p.m., 2–3 p.m., 11 a.m. to 12 p.m., 3–4 a.m., 10–11 a.m., 5–6 p.m., 12–1 p.m., PROPamPEAK, 2–3 a.m.

Coefficients[a].

Model		Unstandardised coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	.108	.119		.904	.366
	SPEED	−.101	.006	−.404	−17.618	.000
	Diary week	.041	.042	.020	.959	.338
	midnight–1 a.m.	−.014	.010	−.029	−1.365	.172
	1–2 a.m.	−.010	.020	−.013	−.490	.625
	2–3 a.m.	.034	.054	.060	.625	.532
	3–4 a.m.	−.036	.069	−.049	−.523	.601
	5–6 a.m.	−.013	.005	−.053	−2.520	.012
	6–7 a.m.	−.005	.003	−.044	−1.926	.054
	7–8 a.m.	−.012	.002	−.181	−6.732	.000
	8–9 a.m.	−.011	.002	−.184	−6.700	.000
	9–10 a.m.	−.010	.002	−.147	−5.328	.000
	10–11 a.m.	−.007	.002	−.092	−2.977	.003
	11 a.m. to 12 p.m.	−.007	.002	−.100	−3.080	.002
	12–1 p.m.	−.005	.002	−.068	−2.198	.028
	1–2 p.m.	−.004	.002	−.045	−1.675	.094
	2–3 p.m.	−.009	.002	−.101	−3.883	.000
	3–4 p.m.	−.004	.002	−.044	−1.791	.074
	4–5 p.m.	−.008	.002	−.108	−3.991	.000
	5–6 p.m.	−.011	.002	−.172	−5.732	.000
	6–7 p.m.	−.010	.002	−.155	−5.339	.000
	7–8 p.m.	−.009	.002	−.097	−4.154	.000
	8–9 p.m.	−.010	.003	−.082	−3.682	.000
	9–10 p.m.	−.010	.003	−.062	−2.859	.004
	10–11 p.m.	−.008	.004	−.047	−2.174	.030
	11 p.m. to 12 a.m.	−.011	.006	−.041	−1.960	.050
	Participant lives in London	−.024	.045	−.012	−.536	.592
	Weekend dummy variable	−.162	.085	−.045	−1.907	.057
	Gender dummy variable	.061	.046	.029	1.329	.184
	Respondent 55+	−.210	.069	−.067	−3.055	.002
	PROPamPEAK	.273	.144	.071	1.889	.059
	PROPpmPEAK	.161	.164	.041	.978	.328

[a] Dependent variable: Log (inc per mile).

Third regression model.

Variables entered/removed[a].

Model	Variables entered	Variables removed	Method
1	Is other type incident, Incident between 6 and 7 p.m., Week of Diary, Buses/coaches involved?, Other vehicles involved?, Is tailgating incident, Is dooring incident, SPEED, Is driveat incident, Vans involved?, Incident between 4 and 5 p.m., HGVs involved?, TTOTAL, Is hook incident, Taxis involved?, Incident between 9 and 10 a.m., Other cyclists involved?, Peds involved?, Motorcycles involved?, Aged over 55, Incident between 5 and 6 p.m., Is pulling out incident, Incident between 7 and 8 a.m., Incident in London?, Dummy Gender variable, Cars involved?, Weekend dummy, Incident between 8 and 9 a.m., Is pass incident[b]		Enter

[a] Dependent variable: how scary.
[b] All requested variables entered.

Model summary.

Model	R	R square	Adjusted R square	Std. error of the estimate
1	.412[a]	.170	.164	.915

[a] Predictors: (Constant), Is other type incident, Incident between 6 and 7 p.m., Week of Diary, Buses/coaches involved?, Other vehicles involved?, Is tailgating incident, Is dooring incident, SPEED, Is driveat incident, Vans involved?, Incident between 4 and 5 p.m., HGVs involved?, TTOTAL, Is hook incident, Taxis involved?, Incident between 9 and 10 a.m., Other cyclists involved?, Peds involved?, Motorcycles involved?, Aged over 55, Incident between 5 and 6 p.m., Is pulling out incident, Incident between 7 and 8 a.m., Incident in London?, Dummy Gender variable, Cars involved?, Weekend dummy, Incident between 8 and 9 a.m., Is pass incident.

ANOVA[a].

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	663.890	29	22.893	27.336	.000[b]
	Residual	3247.696	3878	.837		
	Total	3911.586	3907			

[a] Dependent variable: how scary.
[b] Predictors: (Constant), Is other type incident, Incident between 6 and 7 p.m., Week of Diary, Buses/coaches involved?, Other vehicles involved?, Is tailgating incident, Is dooring incident, SPEED, Is driveat incident, Vans involved?, Incident between 4 and 5 p.m., HGVs involved?, TTOTAL, Is hook incident, Taxis involved?, Incident between 9 and 10 a.m., Other cyclists involved?, Peds involved?, Motorcycles involved?, Aged over 55, Incident between 5 and 6 p.m., Is pulling out incident, Incident between 7 and 8 a.m., Incident in London?, Dummy Gender variable, Cars involved?, Weekend dummy, Incident between 8 and 9 a.m., Is pass incident.

Coefficients[a].

Model		Unstandardised coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	.771	.079		9.705	.000
	Dummy Gender variable	.032	.034	.015	.939	.348
	Incident between 7 and 8 a.m.	−.009	.055	−.003	−.161	.872
	Incident between 8 and 9 a.m.	−.018	.043	−.008	−.421	.674
	Incident between 5 and 6 p.m.	−.015	.051	−.005	−.303	.762
	Incident between 6 and 7 p.m.	.150	.055	.046	2.728	.006
	Incident between 9 and 10 a.m.	−.032	.056	−.009	−.572	.567
	Incident between 4 and 5 p.m.	.089	.068	.021	1.315	.188

Incident in London?	.007	.032	.004	.232	.816
Weekend dummy	.212	.062	.055	3.414	.001
TTOTAL	.000	.000	.028	1.742	.082
SPEED	.009	.004	.034	2.126	.034
Peds involved?	−.134	.049	−.045	−2.746	.006
Other cyclists involved?	−.104	.043	−.037	−2.436	.015
Motorcycles involved?	.116	.087	.020	1.328	.184
Cars involved?	.116	.034	.058	3.376	.001
Taxis involved?	.074	.061	.018	1.202	.229
Vans involved?	.172	.049	.053	3.516	.000
Buses/coaches involved?	.340	.058	.087	5.827	.000
HGVs involved?	.412	.069	.089	5.931	.000
Other vehicles involved?	.155	.065	.035	2.387	.017
Aged over 55	−.080	.053	−.023	−1.510	.131
Week of diary	−.087	.032	−.040	−2.753	.006
Is pass incident	.697	.043	.317	16.345	.000
Is hook incident	.547	.071	.123	7.695	.000
Is pulling out incident	.468	.049	.173	9.557	.000
Is dooring incident	.587	.183	.048	3.209	.001
Is driveat incident	.486	.066	.119	7.353	.000
Is tailgating incident	.615	.114	.082	5.403	.000
Is other type incident	.056	.093	.009	.603	.547

[a] Dependent variable: how scary.

References

Aldred, R., 2012. Governing transport from welfare state to hollow state: the case of cycling in the UK. Transp. Policy 23, 95–102.
Aldred, R., 2013. Incompetent or too competent? Negotiating everyday cycling identities in a motor dominated society. Mobilities 8 (2), 252–271.
Aldred, R., Jungnickel, K., 2012. Constructing mobile places between "leisure" and "transport": a case study of two group cycle rides. Sociology 46, 523–539.
Christmas, S., Helman, S., 2011. Road Sharing: Does It Matter What Road Users Think Of Each Other?.
Daley, M., Rissel, C., 2011. Perspectives and images of cycling as a barrier or facilitator of cycling. Transp. Policy 18 (1), 211–216.
De Geus, B., Degraeuwe, B., Vandenbulcke, G., Panis, L.I., Thomas, I., Aertsens, J., De Weerdt, Y., Torfs, R., Meeusen, R., 2014. Utilitarian cycling in Belgium: a cross-sectional study in a sample of regular cyclists. J. Phys. Act. Health 11 (5), 884–894.
Department for Transport, 2013. Focus on Pedal Cyclists, 2013 [WWW Document]. URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/358042/rrcgb2013-02.pdf (accessed 18.04.15.).
De Hartog, J.J., Boogaard, H., Nijland, H., Hoek, G., 2010. Do the health benefits of cycling outweigh the risks? Environ. Health Perspect. 118 (8), 1109–1116.
DfT, 2014. Reported Road Casualties 2013. DfT, London, Great Britain.
GLA, 2013. Bikes Make up Around a Quarter of Rush-Hour Traffic in Central London, New Survey Shows | London City Hall [WWW Document]. URL https://www.london.gov.uk/media/mayor-press-releases/2013/06/bikes-make-up-around-a-quarter-of-rush-hour-traffic-in-central (accessed 18.04.15.).
Hollingworth, M.A., Harper, A.J.L., Hamer, M., 2015. Risk factors for cycling accident related injury: the UK cycling for health survey. J. Transp. Health, http://dx.doi.org/10.1016/j.jth.2015.01.001, in press.
Horton, D., 2007. Fear of cycling. In: Horton, D., Rosen, P., Cox, P. (Eds.), Cycling in Society. Ashgate, Aldershot, pp. 134–152.
Jacobsen, P., 2003. Safety in numbers: more walkers and bicyclists, safer walking and bicycling. Inj. Prev. 9, 205–209.
Johansson, Ö., Wanvik, P.O., Elvik, R., 2009. A new method for assessing the risk of accident associated with darkness. Accid. Anal. Prev. 41, 809–815.
Joshi, M.S., Senior, V., Smith, G.P., 2001. A diary study of the risk perceptions of road users. Health Risk Soc. 3 (3), 261–279.
Juhra, C., Wieskötter, B., Chu, K., Trost, L., Weiss, U., Messerschmidt, M., Malczyk, A., Heckwolf, M., Raschke, M., 2012. Bicycle accidents - do we only see the tip of the iceberg? A prospective multi-centre study in a large German city combining medical and police data. Injury 43 (12), 2026–2034.
Keep, M., 2013. Road Cycling Statistics. House of Commons Library, London, Standard Note: SN/SG/06224.
Love, D.C., Breaud, A., Burns, S., Margulies, J., Romano, M., Lawrence, R., 2012. Is the three-foot bicycle passing law working in Baltimore, Maryland? Accid. Anal. Prev. 48, 451–456.
Mindell, J.S., Leslie, D., Wardlaw, M., 2012. Exposure-based, 'like-for-like' assessment of road safety by travel mode using routine health data. PLoS One 7 (12), e50606, http://dx.doi.org/10.1371/journal.pone.0050606.
Pooley, C.G., Horton, D., Scheldeman, G., Mullen, C., Jones, T., Tight, M., Jopson, A., Chisholm, A., 2013. Policies for promoting walking and cycling in England: a view from the street. Transp. Policy 27, 66–72. http://dx.doi.org/10.1016/j.tranpol.2013.01.003.
Pucher, J., Buehler, R., 2008. Making cycling irresistible: lessons from The Netherlands, Denmark and Germany. Transp. Rev. 28 (4), 495–528.
Sanders, R.L., 2015. Perceived traffic risk for cyclists: the impact of near miss and collision experiences. Accid. Anal. Prev. 75, 26–34.
TfL, 2012. Levels of Collision Risk in Greater London. TfL, London: ⟨http://www.tfl.gov.uk/cdn/static/cms/documents/levels-of-collision-risk-greater-london.pdf⟩ (accessed 23.03.15.).
Thompson, J., Savino, G., Stevenson, M., 2015. Reconsidering the safety in numbers effect for vulnerable road users: an application of agent-based modeling. Traffic Inj. Prev. 16, 147–153.
Tin Tin, S., Woodward, A., Ameratunga, S., 2013. Completeness and accuracy of crash outcome data in a cohort of cyclists: a validation study. BMC Public Health 13, 420.
Walker, I., 2007. Drivers overtaking bicyclists: objective data on the effects of riding position, helmet use, vehicle type and apparent gender. Accid. Anal. Prev. 39, 417–425.
Walker, I., Garrard, I., Jowitt, F., 2014. The influence of a bicycle commuter's appearance on drivers' overtaking proximities: an on-road test of bicyclist stereotypes, high-visibility clothing and safety aids in the United Kingdom. Accid. Anal. Prev. 64, 69–77. http://dx.doi.org/10.1016/j.aap.2013.11.007.
Wardlaw, M.J., 2014. History, risk, infrastructure: perspectives on bicycling in the Netherlands and the UK. J. Transp. Health 1, 243–250.
Woodcock, J., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., Beevers, S., Chalabi, Z., Chowdhury, Z., Cohen, A., Franco, O.H., Haines, A., Hickman, R., Lindsay, G., Mittal, I., Mohan, D., Tiwari, G., Woodward, A., Roberts, I., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. Lancet 374, 1930–1943.
York, I., Tong, S., 2014. Off-Street Trials of a Bus Stop Bypass: An Assessment of User Perceptions, Safety, Capacity and Accessibility. TRL/TfL, London: ⟨http://www.trl.co.uk/media/573524/ppr730_bus_stop_bypass_main_report_v1.pdf⟩ (accessed 23.03.15).