Investigating cycling kinematics and braking maneuvers in the real world: e-bikes make cyclists move faster, brake harder, and experience new conflicts

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Abstract

Pedelecs (e-bikes), which facilitate higher speeds with less effort in comparison to traditional bicycles (t-bikes), have grown considerably in popularity in recent years. Despite the large expansion of this new transportation mode, little is known about the behavior of e-cyclists, or whether cycling an e-bike increases crash risk and the likelihood of conflicts with other road users, compared to cycling on t-bikes. In order to support the design of safety measures and to maximize the benefits of e-bike use, it is critical to investigate the real-world behavior of riders as a result of switching from t-bikes to e-bikes.

Naturalistic studies provide an unequaled method for investigating rider cycling behavior and bicycle kinematics in the real world in which the cyclist regularly experiences traffic conflicts and may need to perform avoidance maneuvers, such as hard braking, to avoid crashing. In this paper we investigate cycling kinematics and braking events from naturalistic data to determine the extent to which cyclist behavior changes as a result of transferring from t-bikes to e-bikes, and whether such change influences cycling safety.

Data from the BikeSAFE and E-bikeSAFE naturalistic studies were used in this investigation to evaluate possible changes in the behavior of six cyclists riding t-bikes in the first study and e-bikes in the second one. Individual cyclists' kinematics were compared between bicycle types. In addition, a total of 5092 braking events were automatically extracted after identification of dynamic triggers. The 286 harshest braking events (136 cases for t-bike and 150 for e-bike) were then validated and coded via video inspection.

Results revealed that each of the cyclists rode faster on the e-bike than on the t-bike, increasing his/her average speed by 2.9-5.0 km/h. Riding an e-bike also increased the probability to unexpectedly have to brake hard (odds ratio = 1.72). In addition, the risk of confronting abrupt braking and sharp deceleration were higher when riding an e-bike than when riding a t-bike.

Our findings provide evidence that cyclists' behavior and the way cyclists interact with other road users change when cyclists switch from t-bikes to e-bikes. Because of the higher velocity, when on e-bikes, cyclists appear to have harder time predicting movements within the traffic environment and, as a result, they need to brake abruptly more often to avoid collisions, compared with cycling on t-bikes. This study provides new insights into the potential impact on safety that a cycling society moving to e-bikes may have, indicating that e-cycling requires more reactive maneuvers than does cycling traditional bicycles and suggesting that any distractive activity may be more critical when riding e-bikes compared to traditional bikes.

Keywords: cycling safety; naturalistic data; electric bicycle; braking; traffic conflict; road user interaction.

1. Introduction

Pedelecs (e-bikes) are electric power-assisted bicycles that have become very popular in the past few years around the world, including China, Europe, Japan and the US (Fishman & Cherry, 2016). Many cities support the use of e-bikes as a means to reduce congestion and pollution (Ji, Cherry, Bechle, Wu, & Marshall, 2012) and increase mobility (Dill & Rose, 2012; Fyhri & Fearnley, 2015), especially for older people and people with limited access to urban public transport (Weinert, Ma, Yang, & Cherry, 2008). Cycling on e-bike requires less effort than cycling on a traditional bicycle (t-bike), enabling greater traveling distance and reducing the effects of such deterrents as wind or challenging terrain.

In most countries, national regulations classify e-bikes as bicycles, so there are fewer restrictions associated with riding e-bikes compared to other motorized vehicles such as minimum age or mandatory licensing (Cherry, Yang, Jones, & He, 2016). Such regulations are generally based on maximum power of the motor (e.g., 250W in Europe and Japan) and maximum speed under power assistance (e.g., 25km/h in Europe, 32km/h in USA and Canada, 20 km/h China (Rose, 2012)) . However, there is little international consensus about which features of the e-bike should guide regulation of e-bike use or how these features relate to safety.

Despite the large expansion of this new transportation mode, it is not yet known whether e-bikes change cycling behavior and whether cycling with an e-bike may increase crash risk and/or induce conflicts with other road users. Previous studies on e-bike safety have focused primarily on the impact of e-bike use on the transportation system (Cherry et al., 2016; Lee, Molin, Maat, & Sierzchula, 2015), differences in risk-taking behavior (Bai, Liu, Chen, Zhang, & Wang, 2013) or the risk of crashes requiring treatment at an emergency department (Schepers, Fishman, Den Hertog, Wolt, & Schwab, 2014). A few studies have investigated cycling behavior analyzing cycling speed. These include survey data (Weinert et al., 2008), controlled field trials (Vlakveld et al., 2015), or GPS and video surveillance measures along specific commuting routes (Cherry & He, 2009; Lin, He, Tan, & He, 2008). However, the methods used in these studies cannot provide an accurate picture of real-world cycling behavior: data from self-report surveys is subjective and may be questionable (self-report data can be biased by factors such as social desirability), and studies limited to specific field trials or routes have limitations for generalizability.

Naturalistic studies provide an unequaled method for investigating cycling behavior in the real world, where cyclists regularly experience traffic conflicts and may need to perform avoidance maneuvers, like hard braking, to avoid crashing. Using naturalistic data the cyclist's real-world behavior can be investigated by assessing cycling kinematics (e.g., operating speeds of cyclists and speed distribution), near misses and conflicts. Unfortunately, naturalistic data have certain limitations which may bias results geographically and demographically.

To date, only a few naturalistic cycling studies have compared cycling behavior on e-bikes versus t-bikes (Dozza, Bianchi Piccinini, & Werneke, 2016; Langford, Chen, & Cherry, 2015; Schleinitz, Petzoldt, Franke-Bartholdt, Krems, & Gehlert, 2017). Langford et al. (2015) used a US university campus bike-sharing fleet to investigate riding speed behavior. Their results suggested that e-cyclists and traditional cyclist have a very similar riding behavior, although they found e-bikes faster than t-bikes on streets and t-bikes faster on shared-use paths. The study by Schleinitz et al. (2017) in Germany showed cyclists circulate faster on pedelecs (e-bikes) than on traditional bicycles. However, the results were inconclusive about effect of e-bikes on operating speed given that authors used a between subject design and the actual differences of the users populations of both type of bicycles might have biased the average speed values. The study of Dozza, Bianchi Piccinini, et al. (2016) in Sweden compared the ways e-cyclists and traditional cyclists interacted with other road users during critical events, suggesting that e-bike users travel faster and interact differently than traditional cyclists. In conclusion, the characteristics of cycling behavior have not been dealt with in depth and there is still some controversy with regard to whether riders behave differently when cycling on e-bikes compared to cycling on t-bikes and whether this difference has implications to safety.

In this study, we compare cycling behavior on e-bikes and t-bikes by analyzing cycling kinematics and braking events at individual level to determine 1) the extent to which cycling behavior changes in switching from t-bikes to e-bikes, and 2) whether such changes influence cycling safety. We analyzed data from the same cyclists using both e-bikes and t-bikes, collected in two different naturalistic cycling studies. Since speed has been shown to be associated with road safety (Elvik, Christensen, & Amundsen, 2004; Milliken et al., 1998), we analyzed speed profiles to characterize individual and overall cycling behavior on these two types of bicycles. Further, as braking is one of the main avoidance maneuvers when cycling (Maier, Pfeiffer, Wehner, & Wrede, 2015), this study investigated braking events as to determine whether e-cyclist brake differently or for different reasons than traditional bikers. By understanding speed profile and braking behavior our aim is to generate estimates of risk for comparing the two bicycle types.

2. Methods

2.1. Naturalistic data

The naturalistic cycling data used for this study were collected in Gothenburg in two studies: BikeSAFE in 2012 (Dozza & Werneke, 2014) and E-bikeSAFE in 2013 (Dozza, Bianchi Piccinini, et al., 2016) which employed traditional bicycles (t-bikes) and pedelec bicycles (e-bikes), respectively. All the data came from participants who had given consent for reusing data in future studies. In order to facilitate comparisons between the two studies and to control for sample bias, in both studies the same types of data were collected using the same equipment and the same participants at the same time of year. For this paper we analyzed the data from the six cyclists who completed both studies (Table 1) providing two weeks of data each cyclist for each study. These six cyclists were regular riders and contributed 28.5 hours of cycling data from t-bikes and 32.5 hours from e-bikes.

Table 1. Demographics of the Participants

ID	Age*	Group Age†	Gender
1	50	Middle-aged	Female
2	50	Middle-aged	Female
3	45	Middle-aged	Female
4	28	Young (<40)	Female
5	35	Young (<40)	Male
6	45	Middle-aged	Male

*Ages referred to year 2013; †'middle-age' definition retrieved from https://www.collinsdictionary.com/dictionary/english/middle-age

2.2 Bicycle instrumentation

Each bicycle was specially equipped with a GPS, two inertial measurement units (IMU - one on the frame and one on the handlebar), two brake sensors (one for each wheel), one forward facing video camera and a data logger which recorded data from all sensors (Figure 1). The e-bikes were also instrumented with a motor (250 W), a control unit, two brake switches, a throttle (only active up to 6 km/h in accordance with European regulations), and a rechargeable battery (Figure 1). Data from all sensors were collected at a 100 Hz sampling frequency, except for the GPS (10 Hz) and camera (30 fps).

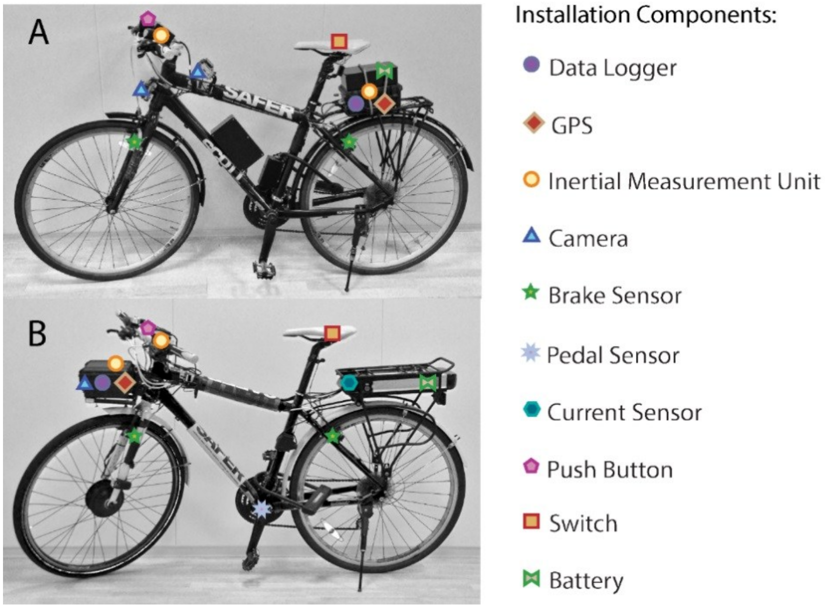

Figure 1. A: Traditional bicycle installation from BikeSAFE. B: Electric bicycle installation from e-bikeSAFE. Source:(Dozza, Werneke, & Mackenzie, 2013).

2.3 Analysis of Cycling Kinematics

Differences in cycling kinematics between the two types of bicycles were assessed by studying the operating speeds and speed distributions both at an individual level (cyclist) and overall for the two types of bicycle (following the approach of Dozza, Werneke, & Mackenzie (2013)). The time spent below 5km/h (speed value close to the stability limit for a bicycle) and above 30km/h (speed limit for bicycles in Sweden) were also computed with regard to stability limits in cycling behavior and Swedish regulations. Paired 2-tail t-tests verified whether the average kinematics for the two types of bicycles were different.

2. 4 Analysis of Braking Events

2.4.1 Identification of Braking Events

Bicycle crashes or near-crashes often happen during braking events; further, during routine cycling, braking is often necessary as an evasive action to respond to unexpected threats. Thus, if cycling kinematics indeed differ between t-bikes and e-bikes, we would expect to find the largest effect on safety during such braking maneuvers. Braking events were identified following the method used by

Johnson et al. (2015) combining analysis of brake pressure (front and rear), braking activation (from switches on e-bikes only), velocity and longitudinal acceleration from the bicycles. Figure 2 shows an example of the data collected during braking events.

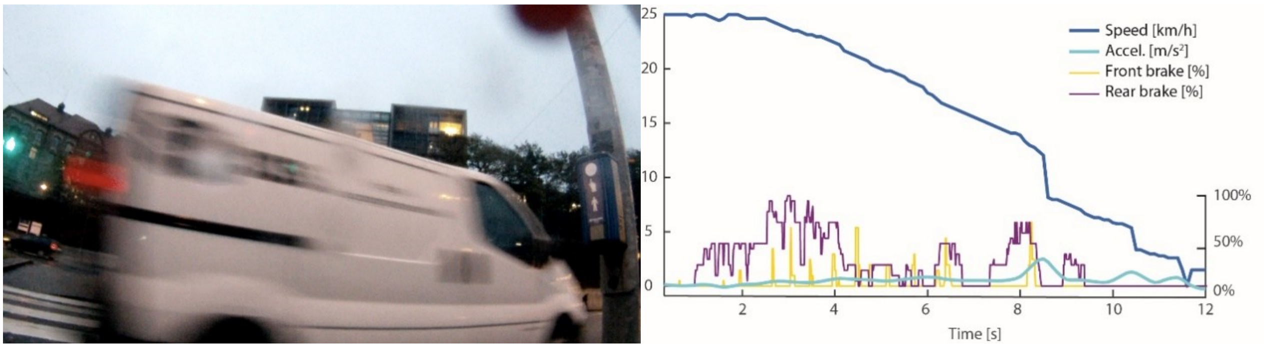

Figure 2. Example of braking. 2a-left) Video Acquisition example; 2b-right) Velocity, brake pressure and deceleration during braking event.

The beginning of each braking event was defined as the time at which acceleration became negative (less than -0.015m/s^2) following an initial velocity higher than 10 km/h, or when the cyclist activated one of the two brakes for at least a 0.4 second duration. Braking ended when the longitudinal acceleration became positive again, or when the cyclist released the brake(s). In some cases, the cyclists activated the brake(s) intermittently within a given braking maneuver. Such short activations were concatenated into a single braking event after video validation of one maneuver.

2.4.2 Selection of the harshest braking events

The harshest braking events - those characterized by higher decelerations and stronger braking pressure - for each cyclist in both datasets were validated by video analysis. To avoid possible bias from over representation of certain cyclists having more braking events, we aimed to balance the number of braking events included for each cyclist and bicycle type. Thus, the harshest braking events were selected among those with highest deceleration per cyclist and type of bike, without setting a threshold. To achieve a high sensitivity in recognizing braking events and to facilitate video validation, sensor data was checked for quality, filtered and synchronized with the video footage before coding. As is common with naturalistic data, not all events were captured with a complete data set (i.e. with all sensors working and sufficient lighting for video coding). Consequently, the number of events for each subject varied in the final data analysis.

2.4.3 Event Coding

Video segments for the braking events were 30 s long, including 25 s before the start of the braking event and 5 s after. Each braking event was validated and coded by one expert analyst, who discussed the uncertain events jointly with a second senior rater before coming to a final assessment, following a procedure similar to that used in other naturalistic studies (Carney, McGehee, Harland, Weiss, & Raby, 2015; Klauer, Dingus, Neale, & Sudweeks, 2006; Schleinitz et al., 2017). Videos were reviewed to code the manoeuver expectancy and the environmental characteristics (Table 2). Manoeuver expectancy identified whether braking was the consequence of a planned behavior to pro-actively regulate speed—planned braking—or, on the contrary, was the reaction to avoid a collision due to a threat or conflict with other road users or obstacles—unplanned braking. Our analysis followed the internationally accepted definition of traffic conflict of Amundsen & Hydén (1977, p. 135): 'A traffic conflict is an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged'. Planned braking events were coded according to the scenario in which the proactive behavior occurred (curve, lane narrowed, expected stop where there is not the right of way… see more in Table 2). Unplanned braking events were further coded by risk level and by type and approach direction of the threat. Coding of a conflict situation for risk level followed criteria similar to those used in the conflict observation technique "DOCTOR" (Grayson, Hyden, Kraay, Muhlrad, & Oppe, 1984; Van Der Horst, De Goede, De Hair-Buijssen, & Methorst, 2014), so traffic conflicts were identified with but using two levels (low and high) instead of five to avoid diluting the braking events.. The classification of 'low risk' is attributed to any anticipatory preventive behavior upon perceiving a potential conflict ('slow conflicts' according to DOCTOR method) and a 'high risk' rating is assigned to serious conflict 'with a more direct link with traffic safety" (Van Der Horst et al., 2014, p361). The level of risk is determined by objective aspects of the conflict situations like distance between the cyclist and the threat at the onset of the braking, bicycle speed, and other factors such as category of opponent road-users and environmental characteristics.

In an effort to verify the consistency and reliability of coding of traffic conflicts, all the braking events from one random cyclist were coded twice, in two sessions 10-days apart to assess the intra-rater reliability. It is worth noticing that, during this coding bicycle type was blind to the rater. The consistency of the video coding was tested using Cohen's kappa for the manoeuver expectancy and for ratings of risk level.

Table 2. Variables coded for braking events

All braking events – Conflict	
Expectancy	unplanned or planned
Unplanned braking events	
Risk level	low (threat present) or high (serious conflict)
Threat type	car, cyclist, pedestrian, heavy-vehicle, motorcycle/moped, animal, or other
Threat approach direction	opposite, left, right, or same
Planned braking events	
Scenario	curve, lane narrows, expected stop, crossing cycle lane/urban road, or other
All braking events - Environment	
Road type	urban road, cycle lane, cycle crossing, sidewalk, or parking lot
Road gradient	flat, downhill, or uphill
Surface type	earth, asphalt, concrete, wood, cobblestone, or undetermined
Light condition	daylight, night (lighted & non lighted), or dawn/dusk

2.4.4 Kinematics of Braking Events

Bicycle velocity at the onset of the braking and deceleration during the braking event were analyzed to provide a quantitative assessment of cyclist behavior during hard braking events.

2.4.5 Statistical Analysis of the Coded Variables

Odds ratio (O.R.) with 95% confidence intervals (C.I. 95%) were used to determine the association between bicycle type and each of the following coded variables: maneuver expectancy, risk level, threat type and planned braking scenario. For the odds ratio analysis, the original categorical variables were recoded as sets of dichotomous variables. In addition, Pearson’s chi-square test was used to assess whether the effect of threat approach direction or environmental variables were different across bicycle type. Finally, the effect of bicycle type and maneuver expectancy on braking kinematics (speed and deceleration) was measured by ANOVA. To meet the requirements for normality and homogeneity of variance for ANOVA analysis (verified with Kolmogorov-Smirnov and Levene tests), a square root transformation was applied to the variable deceleration before the test. Significance levels for all tests were set at $p< .05$.

3. Results

3.1 Cycling kinematics

All cyclists rode faster on e-bikes than on t-bikes, increasing their average speed by 1.5-5.0 km/h, corresponding to 7-31% range in increased speeds (Table 2) and this result was statistically significant (p=.001). When riding e-bikes, cyclists spent less time traveling at speeds below 5 km/h and more time at speeds above 30 km/h compared to riding t-bikes (Table 3). The six cyclists included in this paper were naturally divisible into two groups: one included cyclists who rode below the overall average speed (ID 1-3 in Table 2) and one included cyclists who rode above the average speed (ID 4-6 in Table 3). Note that the group assignments were the same for each cyclist regardless of bike type, suggesting that this division into groups is indeed related to individual cyclist behavior and was not a statistical artifact.

Table 3. Speed and duration per cyclist

Cyclist ID	**t-bike speed** [km/h]	**e-bike speed** [km/h]	**(%)speed<5km/h** t-bike vs e-bike	**(%)speed>30km/h** t-bike vs e-bike	**t-bike data** [min]	**e-bike data** [min]
1	13.0 ± 8.3	15.9 ± 7.8	19.2% vs. 12.4%	2.3% vs. 3.3%	382	274
2	13.7 ± 11.0	17.9 ± 8.3	27.3% vs. 12.6%	6.7% vs. 2.4%	98	230
3	14.0 ± 6.7	18.1 ± 6.7	10.1% vs. 5.7%	1.5% vs. 3.6%	595	341
4	19.6 ± 9.0	21.1 ± 9.1	8.6% vs. 5.9%	7.0% vs. 8.10%	283	283
5	19.7 ± 8.5	23.9 ± 6.1	2.8% vs. 3.0%	5.2% vs. 6.1%	216	397
6	20.3 ± 9.3	25.3 ± 9.0	11.3% vs. 3.0%	12.4% vs. 25.0%	135	424
Average	16.7± 8.4	20.4± 7.8	13.3% vs. 7.0%	5.8% vs. 8.1%	285	325

Figure 3 presents the overall speed distributions for traditional and electrical bicycles (3A), together with the speed distributions for individual cyclists by speed group (3B-C). Figure 3A also includes the standard deviation (SD) calculated for every step of the speed distribution, showing that as speed increases the standard deviation become smaller for e-bikes.

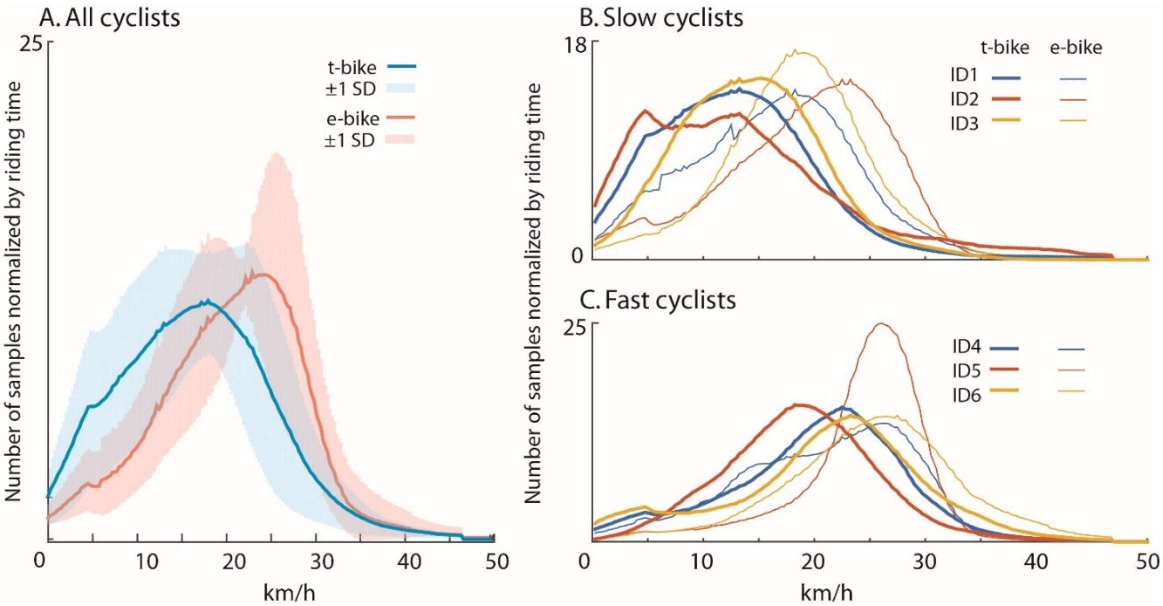

Figure 3. Proportion of time cycling at different speeds (0.25km/h steps) for t-bikes and e-bikes.

3.2 Braking events

A total of 5092 braking events were initially detected using dynamic triggers: 2433 of these were from t-bikes and 2659 from e-bikes. Two datasets of similar size were created respectively for t-bikes and e-bikes (respectively 136 and 150 events). The events were selected among the braking events with the sharpest decelerations, to have a uniform distribution across the participants and not to bias the results. All events in the dataset were next coded via video inspection. Intra-rater reliability analysis with a subset of 19 braking events indicated high consistency for the coding; for braking expectancy Cohen's kappa was 0.872 ($p < .001$) with only one case not consistent due to poor light conditions of the scene, and for the risk level coding Cohen's kappa was 1.0 ($p = .008$) what means total agreement.

Figure 4 shows the geographic distribution of braking events, color coded by bicycle type (Figure 4A) and maneuver expectancy (Figure 4B). In all, 195 braking events were planned, and 91 were unplanned.

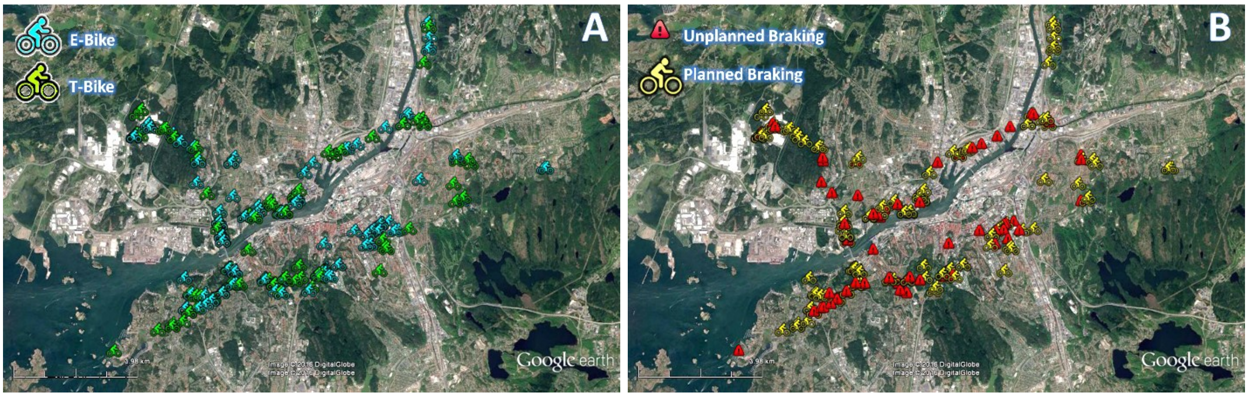

Figure 4. Spatial distribution of the braking events (Gothenburg) by type of bicycle (A) and by braking expectancy (B). This map is from Google Earth provided by DigitalGlobe and CNES/Astrium.

Although the dataset was a selection of the harshest braking events, for each cyclist the majority of braking events were planned, and this finding was independent of bicycle type (Table 4). As Table 4 shows, neither the group (slow vs. fast cyclist) nor the type of bicycle was a predictor for actual number of braking events extracted from the dataset, providing confidence that there was no bias in the distribution.

3.3 Unplanned and planned braking events

Table 4 lists the number of braking events by bicycle type (planned + unplanned) and the proportionate representation of unplanned braking events by subject and overall. Unplanned braking events happened more often on e-bikes than on t-bikes in the overall (O.R. 1.72) and for all six cyclists individually. This result also minimizes the possible effect of the uneven distribution of the sample.

Table 4. Number of braking events and prevalence of unplanned braking events per cyclist.

Cyclist	**Group of**	**t-bike**		**e-bike**	
ID	**Cyclist**	Total	Unplanned	Total	Unplanned
1	Slower	31	26.9%	37	32.4%
2	Slower	11	21.9%	26	30.8%
3	Slower	26	23.5%	34	36.4%
4	Faster	32	32.3%	13	32.4%
5	Faster	19	21.9%	7	30.8%
6	Faster	17	26.3%	33	57.1%
Total		136	25.5%	150	36.7%

In the subset of unplanned braking events, the prevalence of high risk level showed more than two times more likely riding e-bikes than t-bikes. Though, the numbers are too low to report true statistical significance (Table 5). Concerning the threat type, for both t-bikes and e-bikes, car posed the most prevalent threat followed by cyclists and pedestrians, which had a similar prevalence. The prevalence of cyclist as threat is 9.8% higher cycling e-bikes, on the contrary the proportion of cars as threat is 8.2% lower, however these differences were not statistically significant (Table 5). The scenario in which the subset of planned braking events occurred was not different across bicycle type (Table 5).

Table 5. Prevalence and odds ratios by category.

Coding	t- bike	e- bike	O.R. (95% C.I.)
All braking events – Expectancy	N=136	N=150	
Unplanned*	25.7%	37.3%	1.72 (1.04-2.85)*
Unplanned - Risk level	N=35	N=58	
High risk	14.3%	29.3%	2.49 (0.83 -7.49)
Unplanned -Threat type	N=35	N=58	
Car	48.6%	40.4%	0.64 (0.27 – 1.50)
Cyclist	17.1%	26.9%	1.61 (0.55 - 4.68)
Pedestrian	22.9%	23.1%	1.18 (0.39 - 3.55)
Truck/Bus	0.0%	7.7%	--
Motorcycle	5.7%	0.0%	--
Animal	2.9%	0.0%	--
Other	2.9%	1.9%	--
Planned - Scenario	N=101	N=92	
Turning/Crossing	23.8%	34.0%	1.66 (0.89 – 3.10)
Curve	37.6%	26.6%	0.60 (0.33 – 1.11)
Expected Stop	23.8%	24.5%	1.04 (0.54 – 2.00)
Lane narrows	5.0%	6.4%	--
Threat/Road User	3.0%	2.1%	--
Other	6.9%	6.4%	--

*statistically significant when 1.0 does not fall within the 95% C.I.
(--) statistics missing due to insufficient number of data for the analysis

Threat approach direction could not be analyzed as a single grouped variable because not all threats interact with cyclists in the same way. Thus, the effect of threat approach direction was analyzed separately by the three threats that together represented approximately 90% of all the road conflicts: car, cyclist, and pedestrian. Table 6 shows that t-bikes had more unexpected events with car coming from left than e-bikes, however e-bikes had cars coming from left and right in similar proportion. Threats from opponent cyclists traveling along same direction were overrepresented in the e-bike condition.

Table 6. Threat direction distribution for cars, cyclists and pedestrians.

Threat approach direction	car*		cyclist		pedestrian†	
	t-bike N=17	e-bike N=21	t-bike N=6	e-bike N=14	t-bike N=8	e-bike N=12
left	56%	38%	17%	7%	43%	33%
right	6%	48%	0%	0%	0%	50%
same	13%	14%	17%	57%	43%	0%
opposite	25%	0%	67%	36%	14%	17%

* Significant: p<.05; † p=.053 from chi-square test

Finally, the effect of environmental characteristics was not different between e-bikes and t-bikes with the exception of light conditions (Table 7), in which night condition were more prevalent for t-bikes.

Table 7. Environment factors prevalence.

environment	t-bike vs e-bike	*p* (chi-square)
Type of Road	cycle lane (41% vs 39%), urban road (29% vs 27%), cycle crossing (23% vs 31%), parking lot (3% vs 3%), other (4% vs 0%)	0.820
Type of Surface	asphalt (84% vs 95%), cobblestone (11% vs 3%), concrete (4% vs 0%), earth (0% vs 2%), wood (1% vs 0%)	0.085
Road Gradient	flat (71% vs 68%), down (29% vs 30%), up (0% vs 3%)	0.205
Light condition*	daylight (46% vs 59%), dawn/dusk (4%, 20%), night (lighted & non lighted) (50% vs 22%)	0.000*

* Significant at p<.05.

3.4 Kinematics of braking events

Deceleration was higher for e-bikes than for t-bikes (p=.017; Table 8). Deceleration was also higher for unplanned versus planned braking events, however this difference was not statistically significant (p=.078).

Table 8. Mean, standard deviation, and *p* from the ANOVA analysis for maximum deceleration and speed preceding the braking events.

	Planned	Unplanned	*p*	t-bike	e-bike	*p*
Deceleration (m/s²)*	1.8 ± 0.94	2.0 ± 1.21	0.078	1.7 ± 1.01	2.0 ± 1.05	0.017*
Speed (km/h)	20.5± 6.7	21.6± 7.3	0.629	20.8 ± 7.9	21.0 ± 6.3	0.402

* Significant at p<.05.

There was no significant difference in speed between bicycle types (p=.629) nor was there between planned and unplanned events (p=.402). In addition, no interaction was found between the factors type-of-bicycle and maneuver-expectancy for either deceleration (p=.555) or velocity (p=.151).

4. Discussion

The aim of this research was to determine whether cycling behavior changes when cyclists switch from t-bikes to e-bikes and to assess how these changes may increase crash risk or induce conflicts with other road users. Using naturalistic data, we analyzed cyclist behavior across individuals and between bicycle type, comparing operating speed and the risk of facing traffic conflicts after video coding of the harshest braking events. Because the analysis was at an individual level, the effect of type of bicycle on behavior was directly comparable minimizing participant bias. Similarly, since cyclists used the same routes for both naturalistic studies, the data may not suffer from route bias. In addition, there were no differences in the environmental factors (type of road, slope, etc.) on braking events, except for ambient lighting conditions between the two naturalistic studies. Even though both studies were conducted in the fall, the e-bike data collections occurred in lighter conditions because in that season in Sweden daylight duration changes markedly from one month to another. Nevertheless, the fact that speed values preceding the braking events were similar for both bike (and thus lighting) conditions suggests that ambient light levels did not affect riding behavior.

4.1 Cyclists ride faster on e-bikes than on t-bikes

The most notable finding to emerge from this study was that each of the six participants without exception increased the speed between 1.5 and 5.0 km/h moving from t-bikes to e-bikes. This corresponds to an overall average speed increase from 16.7 to 20.4 km/h (increase of 22% in average). Similarly, speed differences on t-bikes compared to e-bikes were found in China along specific commuting routes by Cherry & He (2009) using GPS (11.1 vs. 14.7 km/h) and by Lin et al. (2008) with a video surveillance application (14.8 vs. 21.8 km/h), and in Germany by Schleinitz et al., (2017) in a naturalistic study (15.3 vs. 17.4 km/h). In these three studies, bicycle type was compared using a priori user groups riding their own bicycles, which limits generalizability of results to different user groups. We also found a rising trend to exceed speed legal limits of 30 km/h (for Sweden) when riding e-bikes. This differs from the results of Schleinitz et al. (2017) who found speeds higher than 25 km/h only for the S-pedelec (which provides support up to 45 km/h) and not with the e-bike. Lin et al. (2008) studying circulation in bicycle-exclusive lanes in China, also found that e-bike riders more frequently exceeded the speed limit of 15 km/h stipulated by law. Our findings including the smaller standard deviations found for e-biking at high speed, provide strong evidence that e-bikes condition cycling behavior and encourage cyclist to reach higher speeds.

In addition, the results comparing operating speed reveals that different profiles in cycling behavior exist, including two groups for our study: one faster and one slower. Thus, despite the small sample size, this provides evidence that overall, different types of cyclists are prone to increasing their average speed when riding e-bikes. Lin et al. (2008) obtained similar results in a study on commuting routes in China comparing e-bike and t-bike cyclists. Authors found overall higher average speeds for e-bike cyclists and differences across demographic groups: younger cyclists were faster than elderly ones and males were faster than females. Likewise, Vlakveld et al. (2015) found in their controlled field trials that elderly cyclist were lower than middle aged cyclists with both type of bicycles. This influence of age and gender agrees with the behavior of our groups: the slower group's composition was three middle-aged women and the faster group was made up of two men (one young and another middle-aged) and a young woman. The picture was less clear in previous naturalistic studies that did not include intra-subject comparisons of bicycle type, which this study does. Using a sample primarily composed of university students in the US, Langford et al. (2015) identified separate faster and slower groups for t-bikes but not for e-bikes, for which speed was more homogeneous. In the German study, Schleinitz et al., (2017) showed that riders characterized by lower average speeds, such as older cyclists, are less given to increasing operating speed on e-bikes. The maximum age of our participants was 50 years, so extending our finding to elderly cyclists would require further research. However the trend suggests that speed increases would still exist though by a smaller amount. Even a small increase in operating speed may make elderly people susceptible to increased crash risk. In fact elderly drivers react more slowly to hazards due to reductions in attentional, reflexive and visual capacities (Horswill et al., 2008), and in complex traffic situations elderly cyclists experience a higher mental workload (Vlakveld et al., 2015).

The demographics of the users of e-bikes is a key to understanding the impact of e-bike use on traffic safety. Studies from different regions showed clear differences in e-bike user profiles. On average user groups in Netherlands and Japan are elderly, in North Americans and Australians user age ranges around 40-60 years, and Chinese users tend to be younger (Lee et al., 2015). More demographic research is needed to determine regional e-bike user profiles, and to track changes in e-bike user population as they become more popular as low-cost alternatives for personal mobility.

4.2 Cycling with e-bikes requires more reactive maneuvers than with t-bikes

The second main finding from this research revealed that riding e-bikes increases the probability of having to perform unexpected hard braking in response to threats or traffic conflicts. In addition, the risk level of a conflict during unplanned braking was more often high when riding an e-bike than when riding a traditional bicycle (29% vs.14%). These differences seem to be related to the probability of all cyclists to ride faster on an e-bike.

On the one hand, speed is related to information processing. Higher speed means shorter time window for visual scanning, predicting traffic patterns and reacting; thus increasing the potential for conflicts. This is critical in unexpected events where the amount of information to be processed increases drastically. Consequently, higher speed may convert a typical low risk traffic conflict in a high risk conflict. On the other hand, differences in operating speed affect interactions with other road users due to underestimation of e-bike. Other road users′ underestimating e-bike speed is one of the most common causes of traffic conflicts (Dozza, Bianchi Piccinini, et al., 2016; Haustein & Møller, 2016; Johnson et al., 2015), because of the similarity in appearance to t-bikes and the lack of previous direct experience with e-bike behavior, and the lower pedaling frequency necessary to reach same speed compared to t-bikes (Petzoldt, Schleinitz, Krems, & Gehlert, 2017). Furthermore, we found that instances of unexpected braking in relation to other cyclists riding along same direction were overrepresented in the e-bike condition. The sample size of cyclists as a threat was small (6 cases for t-bikes and 14 for e-bikes respectively), but the results agree with those of Dozza & Bianchi Piccinini (2014) who found that e-cyclists reported a tendency to overtake other cyclists more frequently compared to when riding a t-bike. The results also supports the finding of Hauer (1971) that stated that circulating faster or slower than the median of other road users (t-bikes in the case of cycle lanes) increases the risk of conflicts due to overtaking.

Our results, together with the previous findings, suggest that e-bike cyclists exploit the different kinematic conditions (i.e. higher average speed and decelerations) to implement a different riding behavior. As a consequence they engage in unexpected braking more often during overtaking because they attempt to pass the cyclists without first decreasing speed during the decision and preparation phases (Dozza, Schindler, Bianchi-Piccinini, & Karlsson, 2016). Although the relationship between collisions and traffic conflicts is complex, several studies have found positive relationship between near misses or traffic conflicts and crash risk (Dingus, Hetrick, & Mollenhauer, 1999; El-Basyouny & Sayed, 2013; Guo, Klauer, Hankey, & Dingus, 2010). Accordingly, in our safety analysis, we have used traffic conflicts as surrogates for collisions to estimate risk. The results suggest that riding e-bikes may increase the risk of collision since conflicts are more frequent when riding e-bikes than traditional bicycles.

4.3 Differences in speed and deceleration during braking events

E-bikes in general terms showed higher risk of confronting braking with sharp braking (i.e. higher deceleration). It is worth noting that, the added weight of the electric battery in e-bikes may play a role in a higher risk of losing control during braking. The values of deceleration presented for the unplanned events (mean: 2 m/s^2; SD: 1.2) can be used as reference in identification of unexpected scenarios demanding braking maneuvers. These values also may be contrasted with other naturalistic studies for powered two wheelers like scooters (Baldanzini, Huertas-Leyva, Savino, & Pierini, 2016) that identified patterns related to hard braking with decelerations higher than 2 m/s^2. Contrary to our expectations, speed at the onset of the hard braking events was similar for both e-bikes and t-bikes. Consequently we interpret the finding that the unexpected braking events are more frequent in e-bikes as a result of the higher probability of sustained travel within the critical range of speed (average of 21km/h in our study), rather than just the probability of reaching higher peak velocities.

4.4 Methodological considerations and future research

Participants were selected from a list of volunteers available at SAFER. The list includes researchers active in projects related to traffic safety; however the participants were not aware of the hypotheses of this paper, and the extent to which their behavior deviated from an average cyclist because their profession is unknown. Further, some of the participants did not have previous experience with riding e-bikes. It may, therefore be that they were more cautious riding, especially in the beginning of the study. The low sample size of our study imposes limitations on the generalizability of our results to different groups of riders.

In this study, video coding was mainly performed by a single rater, and only some of the events were coded with the help of a second rater. Employing multiple raters would have made possible to provide information about the inter-rater and intra-rater reliability of the coding scheme used in this paper. Unfortunately, video coding is very time consuming and employing multiple raters makes this procedure even slower and pricier. Common limitations in naturalistic studies related to the methods of data acquisition is consistency in data quality and synchronization. This can affect the number of useable trials (braking events) that can be extracted (which may vary by individual). In our braking event analysis, we only included subjects whose data provided a minimum number of braking events per bicycle type (see Table 4) to obtain a representative sample of their braking behavior. The events were analyzed by personnel blind to the hypothesis of the present research. In addition, upon check of the intra- rater reliability, both the type of bike and rider were blind to the rater and the sequence of events was randomized.

The finding that each individual rider increased their probability of unplanned braking with e-bikes, provides confidence in the robustness of the data, despite the unequal sample sizes. Finally, generalizability will require further studies using larger sample sizes across different cultural infrastructural contexts which could alter results. For example, Gothenburg is characterized by an infrastructure with numerous cycle-lanes, cities like Utrecht in the Netherlands have a large network of cycle lanes frequently segregated and not shared with pedestrians and other cities like Brisbane in Australia have on-road, narrow and discontinuous cycling lanes where cyclists regularly share the space with motorists (Chataway, Kaplan, Nielsen, & Prato, 2014).

4.5 Countermeasures

The implications of our findings suggest certain countermeasures to guarantee safe use of e-bikes as they increase in popularity. To avoid involuntary high operating speed riding e-bikes, implementation of speed control interface or torque control system on e-bikes that increase the pedaling effort as speed increases or as speed limits are exceeded, would help to let the cyclist, not the e-bike, choose the speed. The risk of more abrupt deceleration with e-bikes points the need of equipping e-bikes with brake systems that improve the stopping power while maintaining stability, especially for wet conditions.

In order to avoid underestimating speed issue due to similarities with t-bikes, distinctive design element on the front or side of the bike such as a special shape or light, or future cooperative warning systems running on smartphone (e.g., Gustafsson, Muñoz, Lindgren, Boda, & Dozza, 2013) or V2X communications exchanging data on vehicle type and speed could be implemented to alert other road users that e-bikes travel faster than t-bikes.

A number of studies have found that cyclists lack necessary knowledge of traffic rules (Bai et al., 2013; Langford et al., 2015; Lin et al., 2008). Thus, if e-bikes pose a higher risk of collision than t-bikes, education programs about road rules, rights and responsibilities, skill training or licensing requirements may provide solutions to improve cycling behavior and increase safety.

Finally, with the expected increase of e-bike users in the coming years, the creation of wider cycle lanes would reduce the risks of collision due to bicycle traffic congestion. Wider cycle lanes would also reduce the risk during overtaking. However, if such a measure allowed e-bikes to travel even faster in cycle lanes frequently shared with pedestrians, e-bikes should be speed limited or alternatively circulate in a separated lane.

5. Conclusions

The results presented in this research are the first to evaluate with naturalistic studies the behavior of individual cyclists cycling on t-bikes and e-bikes. Our findings provide evidence that individual cyclist behavior and interactions with other road users change when cyclists switch from t-bikes to e-bikes. Riding an e-bike makes cyclists faster, and almost doubles the chance of having to perform an unplanned braking maneuver in response to a traffic conflict. Cyclists brake harder on e-bikes than on traditional bicycles, even when riding at the same speed, suggesting that e-bikes induce reactive (as opposed to pro-active) braking to avoid conflicts. Because of the higher speed and the more reactive behavior, e-cyclists may be at even higher risk of accident than traditional cyclists when visibility is limited (preventing planning) or if the path is narrow or obstructed (hindering overtaking maneuvers or requiring sudden avoidance maneuvers). Distracting activities, such as talking on a cellphone may also be particularly challenging for e-cyclists because of increased cognitive load, competing coordination tasks, and interference with visual scanning of the surroundings. The results of this study represents advancements in understanding of e-bike cycling behavior and offer new insights on the implications for traffic safety as a cycling community moves to e-bikes.

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References

Amundsen, F. H. E., & Hydén, C. H. (1977). *Proceedings of the First Workshop on Traffic Conflicts*. Oslo/Lund.

Bai, L., Liu, P., Chen, Y., Zhang, X., & Wang, W. (2013). Comparative analysis of the safety effects of electric bikes at signalized intersections. *Transportation Research Part D: Transport and Environment*, *20*, 48–54. https://doi.org/10.1016/j.trd.2013.02.001

Baldanzini, N., Huertas-Leyva, P., Savino, G., & Pierini, M. (2016). Rider Behavioral Patterns in Braking Manoeuvres. *Transportation Research Procedia*, *14*, 4374–4383. https://doi.org/10.1016/j.trpro.2016.05.359

Carney, C., McGehee, D. V, Harland, K., Weiss, M., & Raby, M. (2015). Using Naturalistic Driving Data to Assess the Prevalence of Environmental Factors and Driver Behaviors in Teen Driver Crashes (March 2015), (Washington, DC: AAA Foundation for Traffic Safety).

Chataway, E. S., Kaplan, S., Nielsen, T. A. S., & Prato, C. G. (2014). Safety perceptions and reported behavior related to cycling in mixed traffic: A comparison between Brisbane and Copenhagen. *Transportation Research Part F: Traffic Psychology and Behaviour*, *23*, 32–43. https://doi.org/10.1016/j.trf.2013.12.021

Cherry, C., & He, M. (2009). Alternative Methods of Measuring Operating Speed of Electric and Traditional Bikes in China-Implications for Travel Demand Models. *Proceedings of the Eastern Asia Society for Transportation Studies*, *7*(7).

Cherry, C., Yang, H., Jones, L. R., & He, M. (2016). Dynamics of electric bike ownership and use in Kunming, China. *Transport Policy*, *45*, 127–135. https://doi.org/10.1016/j.tranpol.2015.09.007

Dill, J., & Rose, G. (2012). Electric Bikes and Transportation Policy. *Transportation Research Record: Journal of the Transportation Research Board*, *2314*(Transportation Research Board of the National Academies, Washington, D.C.), 1–6. https://doi.org/10.3141/2314-01

Dingus, T. A., Hetrick, S., & Mollenhauer, M. (1999). Empirical Methods in Support of Crash Avoidance Model Building and Benefits Estimation. *Journal of Intelligent Transportation System*, *5*(2), 93–125.

Dozza, M., & Bianchi Piccinini, G. F. (2014). Do cyclists on e bikes behave differently than cyclists on traditional bicycles? In *Proceedings, International Cycling Safety Conference*. Göteborg, Sweden.

Dozza, M., Bianchi Piccinini, G. F., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 217–226. https://doi.org/10.1016/j.trf.2015.04.003

Dozza, M., Schindler, R., Bianchi-Piccinini, G., & Karlsson, J. (2016). How do drivers overtake cyclists? *Accident Analysis and Prevention*, *88*, 29–36. https://doi.org/10.1016/j.aap.2015.12.008

Dozza, M., & Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? *Transportation Research Part F: Traffic Psychology and Behaviour*, *24*(March), 83–91. https://doi.org/10.1016/j.trf.2014.04.001

Dozza, M., Werneke, J., & Mackenzie, M. (2013). e-BikeSAFE: A Naturalistic Cycling Study to understand how electrical bicycles change cycling behaviour and influence safety. In *Proceedings, International Cycling Safety Conference*. Helmond, The Netherlands.

El-Basyouny, K., & Sayed, T. (2013). Safety performance functions using traffic conflicts. *Safety Science*, *51*(1), 160–164. https://doi.org/10.1016/j.ssci.2012.04.015

Elvik, R., Christensen, P., & Amundsen, A. (2004). *Speed and Road Accidents. An evaluation of the Power Model. TOI Report 740. Institute of Transport Economics of Norway*.

Fishman, E., & Cherry, C. (2016). E-bikes in the Mainstream: Reviewing a Decade of Research. *Transport Reviews*, *36*(1), 72–91. https://doi.org/10.1080/01441647.2015.1069907

Fyhri, A., & Fearnley, N. (2015). Effects of e-bikes on bicycle use and mode share. *Transportation Research*

Part D: Transport and Environment, *36*, 45–52. https://doi.org/10.1016/j.trd.2015.02.005

Grayson, G. B., Hyden, C., Kraay, J. H., Muhlrad, N., & Oppe, S. (1984). *The Malmö study: a calibration of traffic conflict techniques. A study organised by ICTCT (The International Committee on Traffic Conflict Techniques).*

Guo, F., Klauer, S. G., Hankey, J. M., & Dingus, T. a. (2010). Near Crashes as Crash Surrogate for Naturalistic Driving Studies. *Transportation Research Record: Journal of the Transportation Research Board*, *2147*(1), 66–74. https://doi.org/10.3141/2147-09

Gustafsson, P., Muñoz, J. C., Lindgren, L., Boda, C., & Dozza, M. (2013). BikeCOM – A cooperative safety application supporting cyclists and drivers at intersections. *Proceedings of the 3rd Conference of Driver Distraction and Inattention, Gothenburg, Sweden*, (2), 1–16.

Hauer, E. (1971). Accidents , Overtaking and Speed Control. *Accident Analysis & Prevention*, *3*(1), 1–13.

Haustein, S., & Møller, M. (2016). E-bike safety: Individual-level factors and incident characteristics. *Journal of Transport and Health*, *3*(3), 386–394. https://doi.org/10.1016/j.jth.2016.07.001

Horswill, M. S., Marrington, S. A., McCullough, C. M., Wood, J., Pachana, N. A., McWilliam, J., & Raikos, M. K. (2008). The hazard perception ability of older drivers. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *63*(4), P212–P218. https://doi.org/63/4/P212 [pii]

Ji, S., Cherry, C. R., Bechle, M. J., Wu, Y., & Marshall, J. D. (2012). Electric vehicles in China : emissions and health impacts. *Enviromental Science and Technology*, *46*(4), 2018–2024.

Johnson, M., Chong, D., Carroll, J., Katz, R., Oxley, J., & Charlton, J. (2015). *Naturalistic cycling study: identifying risk factors for cyclists in the Australian Capital Territory. Report No. 322*. Melbourne. Monash University Accident Research Centre.

Klauer, S., Dingus, T., Neale, V., & Sudweeks, J. (2006). The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. *US Department of Transportation*, (April), 226. Retrieved from https://vtechworks.lib.vt.edu/handle/10919/55090

Langford, B. C., Chen, J., & Cherry, C. R. (2015). Risky riding: Naturalistic methods comparing safety behavior from conventional bicycle riders and electric bike riders. *Accident Analysis and Prevention*, *82*, 220–226. https://doi.org/10.1016/j.aap.2015.05.016

Lee, A., Molin, E., Maat, K., & Sierzchula, W. (2015). Transportation Research Record: Electric Bicycle Use and Mode Choice in the Netherlands. *Journal of the Transportation Research Board. Transportation Research Board*, (2520), 1–7. https://doi.org/10.3141/2520-01

Lin, S., He, M., Tan, Y., & He, M. (2008). Comparison study on operating speeds of electric bicycles and bicycles: experience from field investigation in Kunming, China. *Transportation Research Record: Journal of the Transportation Research Board*, (2048), 52–59.

Maier, O., Pfeiffer, M., Wehner, C., & Wrede, J. (2015). Empirical Survey on Bicycle Accidents to estimate the Potential Benefits of Braking Dynamics Assistance Systems. *International Cycling Safety Conference. Hannover, Germany*.

Milliken, J. G., Council, F. M., Gainer, T. W., Garber, N. J., Gebbie, K. M., Hall, J. W., … Weaver, R. P. (1998). Managing speed: review of current practice for setting and enforcing speed limits. *Transportation Research Board. Committee for Guidance on Setting and Enforcing Speed Limits*, Special Report 254.

Petzoldt, T., Schleinitz, K., Krems, J. F., & Gehlert, T. (2017). Drivers' gap acceptance in front of approaching bicycles - Effects of bicycle speed and bicycle type. *Safety Science*, *92*, 283–289. https://doi.org/10.1016/j.ssci.2015.07.021

Rose, G. (2012). E-bikes and urban transportation: Emerging issues and unresolved questions. *Transportation*, *39*(1), 81–96. https://doi.org/10.1007/s11116-011-9328-y

Schepers, J. P., Fishman, E., Den Hertog, P., Wolt, K. K., & Schwab, A. L. (2014). The safety of electrically assisted bicycles compared to classic bicycles. *Accident Analysis and Prevention*, *73*, 174–180. https://doi.org/10.1016/j.aap.2014.09.010

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & Gehlert, T. (2017). The German Naturalistic Cycling Study - Comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science*, *92*, 290–297. https://doi.org/10.1016/j.ssci.2015.07.027

Van Der Horst, A. R. A., De Goede, M., De Hair-Buijssen, S., & Methorst, R. (2014). Traffic conflicts on bicycle paths: A systematic observation of behaviour from video. *Accident Analysis and Prevention*, *62*, 358–368. https://doi.org/10.1016/j.aap.2013.04.005

Vlakveld, W. P., Twisk, D., Christoph, M., Boele, M., Sikkema, R., Remy, R., & Schwab, A. L. (2015). Speed choice and mental workload of elderly cyclists on e-bikes in simple and complex traf fi c situations : A fi eld experiment. *Accident Analysis and Prevention*, *74*, 97–106. https://doi.org/10.1016/j.aap.2014.10.018

Weinert, J. X., Ma, C., Yang, X., & Cherry, C. R. (2008). Electric Two-Wheelers in China: Effect on Travel Behavior, Mode Shift, and User Safety Perceptions in a Medium-Sized City. *Transportation Research Record: Journal of the Transportation Research Board*, *2038*(1), 62–68. https://doi.org/10.3141/2038-08