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A data-driven framework for the safe integration of micro-mobility into the transport system: Comparing bicycles and e-scooters in field trials

Marco Dozza *, Alessio Violin, Alexander Rasch

Chalmers University of Technology, Sweden

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ABSTRACT

Introduction: Recent advances in technology create new opportunities for micro-mobility solutions even as they pose new challenges to transport safety. For instance, in the last few years, e-scooters have become increasingly popular in several cities worldwide; however, in many cases, the municipalities were simply unprepared for the new competition for urban space between traditional road users and e-scooters, so that bans became a necessary, albeit drastic, solution. In many countries, traditional vehicles (such as bicycles) may not be intrinsically safer than e-scooters but are considered less of a safety threat, possibly because—for cyclists—social norms, traffic regulations, and access to infrastructure are established, reducing the number of negative stakeholders. Understanding e-scooter kinematics and e-scooterist behavior may help resolve conflicts among road users, by favoring a data-driven integration of these new e-vehicles into the transport system. In fact, regulations and solutions supported by data are more likely to be acceptable and effective for all stakeholders. As new personal-mobility solutions enter the market, e-scooters may just be the beginning of a micro-mobility revolution. *Method:* This paper introduces a framework (including planning, execution, analysis, and modeling) for a data-driven evaluation of micro-mobility vehicles. The framework leverages our experience assessing bicycle dynamics in real traffic to make objective and subjective comparisons across different micro-mobility solutions. In this paper, we use the framework to compare bicycles and e-scooters in field tests. *Results:* The preliminary results show that e-scooters may be more maneuverable and comfortable than bicycles, although the former require longer braking distances. *Practical Applications:* Data collected from e-scooters may, in the short term, facilitate policy making, geo-fencing solutions, and education; in the long run, the same data will promote the integration of e-scooters into a cooperative transport system in which connected automated vehicles share the urban space with micro-mobility vehicles. Finally, the framework and the models presented in this paper may serve as a reference for the future assessment of new micro-mobility vehicles and their users' behavior (although advances in technology and novel micro-mobility solutions will inevitably require some adjustments).

1. Introduction

Micro-mobility is a growing phenomenon that challenges the urban transport system (Chang et al., 2019; Zagorskas & Burinskienė, 2020) and the research community (O'Hern & Estgfaeller, 2020). Although new (e-) vehicles with different numbers of wheels and tracks (SAE Committee, 2018) enter the market at a fast pace, e-scooters (powered standing scooters, according to SAFE J3194) are undoubtedly the most popular and controversial micro-mobility solution in today's urban environment (Gössling, 2020). Since 2015, their number has increased exponentially in several cities world-wide (Liew et al., 2020; Møller & Simlett, 2020) raising several safety concerns. A recent report from Fearnley et al. (2020) suggests that the crash risk is 10-fold when riding an e-scooter compared to riding a bicycle, while the Safe Micromobility report for the Organisation for Economic Co-operation and Development reports a much larger number of injuries per trip for e-scooters than for bicycles (Table 2; (International Transport Forum, 2020)), albeit the comparison was only made across different countries.

While sharing systems may have drastically accelerated the success of e-scooters (Møller & Simlett, 2020), research shows that e-scooters met some important needs for personal mobility, surpassing other transport modes (Bird, 2019; Portland Bureau of Transportation, 2018). Typically ridden by young males with an average (or above average) income (6t-bureau de recherche,

* Corresponding author at: Chalmers University of Technology, Hörselgången 4 (Campus Lindholmen, SAGA 4th floor), SE-417 56 Göteborg, Sweden.

E-mail address: marco.dozza@chalmers.se (M. Dozza).

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2019; Bjerkan et al., 2020), e-scooters replace walking as well as other means of transport, promising to reduce the congestion, noise, and carbon footprint of urban transport (Sharkey et al., 2020). Unfortunately, as e-scooters proliferate, so do e-scooterists' visits to the emergency room and, therefore, healthcare costs (Bekhit et al., 2020; Ishmael et al., 2020). Several physicians promptly exposed the unusually high demand that e-scooters place on the healthcare system (Badeau et al., 2019; Bekhit et al., 2020; Namiri et al., 2020). E-scooter injuries occur relatively often (1 per every 26,881 miles according to [8]), mainly in the evenings and on weekends (Stigson et al., 2020; Vernon et al., 2020). These injuries have their own signature, with head and facial injuries being the most common (Beck et al., 2020; Trivedi et al., 2019; Trivedi et al., 2019; Wüster et al., 2020). Although e-scooterists would benefit from using a helmet (Moftakhar et al., 2020) and other protective equipment (Allem & Majmundar, 2019), very few even wear a helmet (Beck et al., 2020; Haworth & Schramm, 2019) despite recommendations from several institutions. (Remarkably, the European Cycling Federation has a long tradition of advocating that helmets *not* be mandatory for cyclists and still recommends e-scooterists using helmets. Buczyński & Fahrenkrug, 2020.) Most e-scooter crashes appear to be single-vehicle crashes (Trafikkontoret, 2009). However, interactions with other road users play an important role (Stigson & Klingegård, 2020; Stockholms Stad, 2019); 80% of e-scooter fatal crashes are collisions with motorized vehicles (International Transport Forum, 2020). Further, Blomberg et al. (2019) report that 17% of the road users injured in e-scooter crashes were non-riders. Interestingly, Austin Public Health reports that more than 30% of the injuries happen during the very first trip with an e-scooter (Austin Public Health, 2019), suggesting that education and training may help improve e-scooter safety. Rider behavior, including intoxication, is also among the causes of e-scooter crashes (Bjerkan et al., 2020; Trafikkontoret, 2009). Nevertheless, field evidence (e.g., from naturalistic studies) is still too sparse, and crash data are still too limited to draw solid conclusions about crash causation and explain the behavioral mechanisms that undermine e-scooter safety.

Concerns about e-scooters are not limited to their safety; the competition for urban space among road users is evident from the low acceptance of e-scooters by the community (Gössling, 2020). The low acceptance is inversely related to age (Ramboll, 2020), possibly because younger people are the main e-scooter users (6t-bureau de recherche, 2019). From an urban perspective, the main concerns are e-scooters that ride on sidewalks, park where they are not supposed to, ride too fast, and generally break rules. Municipalities are on the front line promoting the safe integration of e-scooters into the transport system. Their efforts so far have focused on designating parking zones (so that e-scooters don't park on sidewalks or in bike lanes; Møller & Simlett, 2020) and introducing new regulations (such as prohibiting riding on the sidewalk, requiring users to wear a helmet, or simply limiting the number of e-scooters or operators in the city; Gössling, 2020). Operators of rental sites may improve e-scooter safety by setting limits for users (e.g., with geofencing or a minimum age for riding) and by improving e-scooter design, for instance, by installing reflectors or increasing the wheel size (6t-bureau de recherche, 2019; Møller & Simlett, 2020). So far, behavioral countermeasures include campaigns, regulations on phone use, limits on the maximum blood-alcohol concentration allowed for riders (Gössling, 2020), and training for novice users (Faraji et al., 2020).

Because so many stakeholders (e-scooterists, other road users, authorities, operators, etc.) with conflicting interests are part of the e-scooter revolution and its regulation, it is hard to find countermeasures that accommodate and are accepted by all of them. For instance, speed regulations may feel unnecessary to e-scooterists, while still perceived as an insufficient countermeasure by other road users. It may be easier to obtain buy-in from all stakeholders if the choice of countermeasures is data-driven; in other words, if policies and decisions are rooted in an objective assessment of the (safety) issues (International Transport Forum, 2020). Data from hospital emergency departments and crash databases provide objective evidence to help researchers understand the size of the safety problem at hand; however, although they describe the problem, they do not illustrate the cause of the problem or how to solve it. One way to get closer to the root of the problem is by recording riding data. Operators already do that with GPS, which enables several geographical analyses. These analyses may inform geofencing and help route e-scooters to decrease congestion but, alone, do not give many insights into the safety problem. More sophisticated data, such as naturalistic data (Dingus et al., 2006; Dozza & Werneke, 2014; Westerhuis & De Waard, 2016) and field data (Kovácsová et al., 2016; Lee et al., 2020; Llorca et al., 2014), may provide unique insights leading to novel, more acceptable countermeasures (novel, because these data may highlight previously unknown e-scooter and e-scooterist weaknesses; more acceptable, because any legislation or recommendation backed up by data has a better chance of convincing a wide spectrum of stakeholders).

Instrumented bicycles have been used in several studies to collect data to promote infrastructure design, rider education, and intelligent system design (Dozza & Fernandez, 2013; Gehlert et al., 2012; Hatfield et al., 2017; Kovácsová et al., 2016; Schleinitz et al., 2017; Twisk et al., 2021). Similarly, data may be collected from instrumented e-scooters to unveil the extent to which they compare to other micro-mobility solutions. Very few studies so far have used instrumented e-scooters to investigate how riders maneuver the e-scooters (among them Garman et al., 2020; Löcken et al., 2020).

This paper responds to the call for more research on e-scooters from several organizations such as the International Transport Forum and the Transportation Research Laboratory (International Transport Forum, 2020; Hitchings et al., 2019) by proposing a procedure to measure and compare the kinematics and controls of different micro-mobility vehicles in field trials. The main objective of this paper is to describe this procedure for data collection and analysis and exemplify it with a simple application comparing e-scooters and bicycles in field trials. The procedure is intended to favor repeatability across studies and vehicle types. It includes several steps, from planning the experiment to modeling the data, and is exemplified in this paper by comparing an e-scooter and a bicycle. The final aim of this procedure is to provide policymakers, municipalities, operators, and road authorities with objective evidence to guide their actions for improving micro-mobility. In addition, the reference models that we propose in this paper may inform the design of intelligent systems and cooperative applications, promoting the safe integration of connected automated vehicles into the transport system.

2. Methods

Fig. 1 shows the framework for evaluating and comparing micro-mobility vehicles in field trials. In this section, we describe this procedure step by step and apply it to the specific use case comparing e-scooters and bicycles.

2.1. Maneuvers

Road users keep safe by controlling their *speed* and *heading*. In practice, this means that braking (longitudinal control) and steering (lateral control) help road users avoid collisions. As a conse-

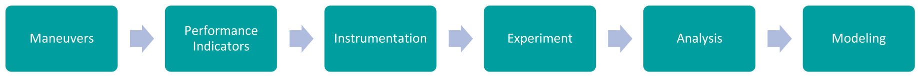

Fig. 1. Methodological steps to plan and perform a field-test comparison across vehicles.

quence, measures such as braking distance and steering angle may therefore provide surrogate safety measures (SAE, 2015). While measures for longitudinal control may be similar across vehicles (because they boil down to braking performance, i.e., how effectively the vehicle can reduce the speed and come to a stop), lateral control measures (i.e., the steering performance) may require vehicle-specific measures and performance indicators. In fact, steering may happen in different ways across micromobility solutions and depend on the vehicle configuration (e.g., number of wheels and tracks). Likewise, avoidance maneuvers, constrained by the vehicle *geometry*, may fundamentally differ across vehicles (e.g., depending on the number of tracks and wheels (Genta & Morello, 2009), especially for steering. Further, *controls* for braking and steering vary greatly across micro-mobility vehicles, independently of the number of tracks and wheels. For instance, the brakes may be hand-controlled (e.g., a sliding knob on a remote control on e-skateboards), foot-controlled (e.g., a foot brake on a scooter), or controlled by leaning (e.g., on a monowheel). Similarly, to steer, users control e-skateboards and monowheels by leaning, Segways by using a handle, and hoverboards by changing their posture. When riding a single-track two-wheeler, as in our use case, the user controls speed and heading by applying the brakes and turning the handlebars.

From a *human-factors* perspective, avoidance maneuvers also differ depending on whether they are *planned* (e.g., slowing down when approaching an intersection) or *unplanned* (e.g., braking abruptly to avoid a road user suddenly crossing in front). Typically, unplanned maneuvers elicit more critical kinematics and threaten vehicle stability more than planned maneuvers (Huertas-Leyva et al., 2018). Speed is also a major factor, as it, too, influences the stability and maneuverability of the vehicles (especially for single-track vehicles; Schwab & Meijaard, 2013). Finally, results from the literature—as well as the need to compromise between safety and maneuvers that are representative—may guide the maneuver selection in a field-trial comparison across vehicles. Defining a set of maneuvers for the comparison across vehicles is therefore a compromise. Ideally, the maneuvers should be representative of lateral and longitudinal control take, into account different vehicle geometries, the subject expectancy, and the vehicle-specific controls. In reality, the most stringent requirement may come from the time needed for collection, which constrains the number of trials. Further, safety and ethical concerns limit the selection of critical avoidance maneuvers. Selecting maneuvers depending on existing literature may be convenient because it enables comparisons (and verification) of the results.

For our use case, we limited our selection to four maneuvers (for fatigue not to confound our results): three required braking and one steering (to address both longitudinal and lateral control). In the braking maneuvers, the participants were asked to brake comfortably or harshly, and, in this latter case, we assessed both maneuvers that could be planned ahead of time and maneuvers that were triggered at a random time (Fig. 2). It is worth mentioning that the difference between comfort and harsh braking is an indication of the braking performance that a road user can achieve when compromising comfort for safety, and the difference between planned and unplanned harsh braking helps determine whether response time alone may predict braking performances in critical situations. Our selection was greatly inspired by the previous literature: the maneuvers that we chose are similar to the ones tested in previous studies (Kovácsová et al., 2016; Lee et al., 2020; Rasch et al., 2016). Further, we included planned and unplanned maneuvers to address expectancy and compare our results with Huertas et al. (2018).

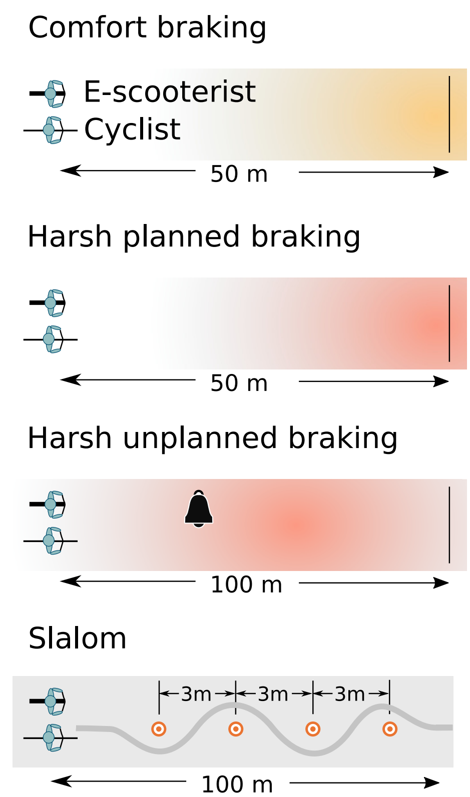

Fig. 2. The four maneuvers selected for the experiment. The red and yellow areas indicate the relative criticality of the maneuver: red is a higher criticality than yellow.

Speed greatly impacts micro-mobility maneuvering and thus should be selected with care during testing, possibly using data from real traffic to make sure the maneuvers tested in the field actually happen in reality as well. In our case, the speed was set to 17 km/h, in line with previous naturalistic studies (Dozza & Werneke, 2014; Schleinitz et al., 2017); lower speeds would have been less critical for braking maneuvers, and higher speeds may not have been as representative. For the steering maneuver, the participants were asked to steer in a slalom among four cones with an approach speed of 7–10 km/h (Fig. 2). It is worth noticing that the speeds selected were also similar to the ones used in previous studies (Kovácsová et al., 2016; Lee et al., 2020; Rasch et al., 2016). The slalom task is complex, requiring the user to steer several times; we selected this task (as opposed to a simple comfortable steering task) to amplify the difference that we expected between e-scooters and bicycles because of the different wheelbase lengths. We selected a low speed to challenge our participants' equilibrium, possibly amplifying the differences across the vehicles. (Although low, this speed is still within the range of speeds found in near-crashes in naturalistic cycling data, and therefore it was assumed to be representative of a normal traffic situation; Dozza, 2013.)

2.2. Performance indicators

The specific strategy that a user applies to control braking and steering is important for the selection of the performance indicators to measure the maneuvers and the subsequent selection of hardware for the instrumentation and data collection. In general, sensors assess braking and steering by acquiring data on vehicle kinematics and controls. Deceleration and jerk are fundamental measures of braking performance (Brännström et al., 2014), whereas angular rate and lateral acceleration are often used to evaluate steering performance (Brännström et al., 2014; Kovácsová et al., 2016). Of course, the geometry of the vehicle and the specific controls that the user must operate to laterally and longitudinally control the vehicle may suggest metrics that are vehicle-specific.

Previous studies on bicycles have indicated that indicators such as braking distance and average deceleration may estimate braking performance (Lee et al., 2020), while steering performance may be evaluated from the steering angle, steering angle rate, roll rate, cross-correlation coefficient (R^2) between roll rate and steering rate, and the time delay between roll rate and steering rate (Kovácsová et al., 2016). We also included mean absolute lateral acceleration as a proxy for comfort.

2.3. Instrumentation

The instrumentation consists of components capable of collecting all the signals needed to calculate the performance indicators. Typically, these components (including sensors, loggers, and power supplies) may require some hardware and software development (Dozza & Fernandez, 2013; Garman et al., 2020). Which sensors are selected for data acquisition depends on the performance indicators that best measure the performance of a maneuver. The sensors may be installed on the vehicle, on the user, or on the infrastructure. Although some vehicles have their own sensors that the experimenter may hack into (for instance, e-bikes have a built-in speed sensor), new sensors may be installed on the vehicle. Of course, the placement of sensors in some vehicles (e.g., monowheels) may present more challenges than in others (e.g., bicycles) simply because of the vehicle's form or the risk of posing a hazard or changing user behavior. It is worth mentioning that although the selection of sensors may be vehicle-specific, the logging part (especially the software) may be portable across vehicles and require only minor adjustments.

To acquire the vehicle kinematics and compute the performance indicators for our use case, we combined an in-vehicle inertial measurement unit (IMU: PhidgetSpatial 3/3/3 1044) and potentiometer with a stationary LiDAR sensor (Hokuyo UXM-30LXHEWA). Fig. 3 shows the installations. The logger was based on a Raspberry Pi 3 model B platform with the same software used by Rasch et al. (2020). The logger was the same for all vehicles and powered by a 5 V 2 A power bank (weight ~ 270 g). The total weight of the in-vehicle instrumentation was about 650 grams (i.e., negligible when compared to the combined vehicle and rider weights). Table 1 describes the performance indicators (two for the braking maneuvers and six for steering). For each indicator, the signal, the relevant sensor, and the interpretation are provided.

2.4. Experiment

Field experiments with instrumented vehicles, like all other experiments, require that the experimental design be carefully considered. However, even well-designed field experiments have unique challenges: they may be affected by the elements and should happen in an area that, while isolated, resembles an urban environment. Further, the use of multiple sensors and loggers typically requires extra care (e.g., pilot experiments) to ensure data quality and synchronization. The inclusion criteria for participants in the experiment may be inspired by the typical user of a specific micro-mobility solution: for instance, e-scooterists are mainly young males. However, since elderly and other populations may be more of a safety concern, individual studies may opt for different inclusion criteria, depending on their specific research questions. Of course, the vehicle manufacturer recommendations (e.g., max height and weight) should also be considered when defining the inclusion criteria.

We obtained approval to run the experiment from the Swedish Ethical Review Authority (Etikprövningsmyndigheten; Ref. 2019-04547). The location of our experiment is presented in Fig. 4. Inclusion criteria required participants to be between 18 and 60 years old (younger subjects were excluded because they represent a minority group that requires extra ethical considerations and approvals, and older subjects were excluded because of their potentially reduced physical capacity; Vlakveld et al., 2015), be capable of riding a bicycle, have no physical disabilities, have never been in a serious traffic crash, and be able to speak English (because we used questionnaires in English). Participants were informed about the study and the potential risk of falling associated with the tasks, and signed a consent form prior to participating.

Six riders (two females) participated in this pilot study. Age, height, and weight ranges were: 23–29 years, 178–188 cm, and 62–80 kg, respectively. Prior to the experiment, each participant rode the e-scooter and the bicycle and performed the four maneuvers until they felt comfortable proceeding with the experiment. The order of the trials was randomized to minimize the effects of learning, adaptation, and habituation.

Subjective data help relate performance indicators to users' perceptions. For instance, for our experiment, we were particularly interested in whether riders were aware of how their braking and steering performances changed across vehicle types. After our experiment, we asked all riders to fill in a questionnaire, using

Fig. 3. Instrumented vehicles.

Table 1
Variables considered for the analysis of braking and steering.

Maneuver	Performance indicators	Signal	Sensor	Relation
Braking	Braking distance	Trajectory	LiDAR	Safety
	Average deceleration	Longitudinal acceleration	IMU	Comfort
Steering	Steering distance	Trajectory	LiDAR	Maneuverability
	Mean absolute steering angle	Handlebar angle	Potentiometer	Balancing
	Mean absolute steering angle rate	Handlebar angle	Potentiometer	Control
	Mean absolute roll rate	Roll rate	IMU	Stability
	Mean absolute lateral acceleration	Lateral acceleration	IMU	Comfort
	Delay between roll rate and steering rate	Roll rate & handlebar angle	IMU & Potentiometer	Maneuverability

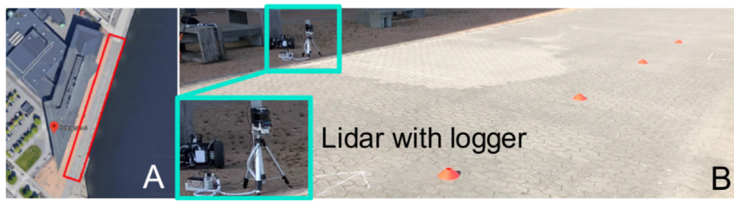

Fig. 4. Experimental setup. Panel A: Birds-eye view of the field trials. Panel B: Setup of the LiDAR and the cones (for the steering trial).

a Likert scale 1–7 (where 1 is very poor and 7 is exceptional) to rank their comfort level during the following vehicle operations: mounting and dismounting; accelerating from stand-still; maintaining low speed; maintaining high speed; keeping their balance at low speed; keeping their balance at high speed; braking at high speed; and steering at low speed. The answers provided us with subjective data about the safety, maneuverability, and comfort of the vehicles that we could compare to our objective data. The questionnaire was adapted from that in Rasch et al. (2016).

2.5. Data analysis

The data analysis depends on the specific sensors and metrics used in the experiment, so it is hard to offer general guidelines that would be useful; therefore, we discuss our use case. (Because IMUs are likely to be a sensor of choice for any vehicle under analysis, the data processing presented below may still be of use for future studies.)

First, we filtered the raw signals using two different techniques. To calculate the trajectories, we used a Rauch-Tung-Striebel smoother (Rauch et al., 1965) which is a sensor fusion algorithm that takes as input the position and derived speed from the LiDAR and the acceleration from the IMU and outputs speed and position. The signal from the potentiometer was converted to a digital signal by means of a 10-bit ADC connected to the data logger. For all the other signals, a low-pass filter with a cut-off frequency of 7.5 Hz was applied. The braking and steering events were then extracted. To determine the start and end of each braking maneuver, we used speed thresholds (16 km/h and 1 km/h, respectively). For the steering maneuvers, we used distance thresholds (1 m before the first cone and 1 m after the last cone). Finally, from these events, we computed the performance indicators summarized in Table 1. The last column in Table 1 is indicative of how each of the indicators was related to safety, maneuverability, stability, balancing, control, and comfort from previous studies.

2.6. Modeling

Modeling is a powerful way to represent complex datasets. Requiring only a few parameters, the models can be adapted and used as references for comparisons in future studies (Morando et al., 2019). Mathematical models also enable predictions, which is particularly important for advanced driver assistance systems or automated connected vehicles that must be able to predict other road users' intentions to safely maneuver in traffic (Rasch & Dozza, 2020; Boda et al., 2020). Models are, of course, maneuver-specific and should be the same across vehicle types, to enable comparisons. Nevertheless, different vehicle types may elicit different strategies for braking and/or steering, which should be considered when interpreting the models because it may drastically affect the models' validity. Braking was modeled according to Lee et al. (2020), with a linear regression illustrating the average deceleration of the maneuvers. However, we did not use their model for steering because the slalom task differed significantly from their task (steering avoidance). We first tried to fit their Gaussian model on the first steering action (circumventing the first cone), but the fit was not reasonable because the presence of the second cone created a constraint on the first steering maneuver, skewing the maneuver's shape. As a result, we created a steering model that captures the more complex vehicle dynamics as the participant circumvents the cones. This model fits a sine wave to the slalom trajectory using three parameters: amplitude (α), frequency (ω), and phase (ϕ) (Eq. (1)). The sine wave amplitude explains the proximity to the cone (and is therefore a surrogate for the trajectory's curvature) and its frequency describes the change of direction that was constrained by the cone placement. Finally, the sine wave phase indicates the distance from the first cone at which the rider initiated the steering maneuver. It is worth noting that while helping exemplify our framework, this modeling effort provides some preliminary reference models for the prediction of e-scooter maneuvers and the comparison among micro-mobility vehicles.

$$y(t) = \alpha * \sin(\omega * t + \phi) \tag{1}$$

3. Results

This section presents the results from our pilot study that exemplified the framework presented in this paper. The ballpark results in this section are intended as a reference for future studies.

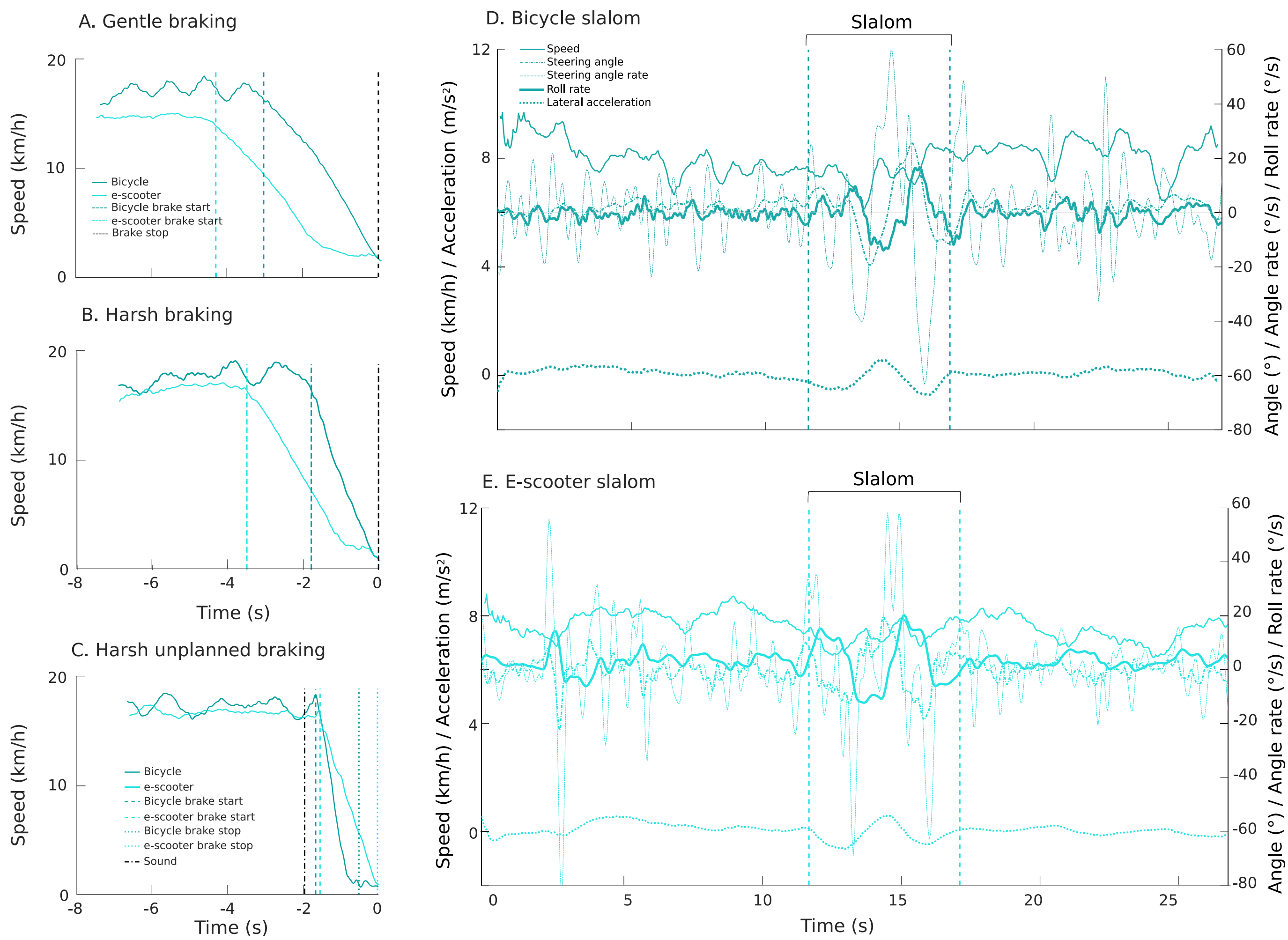

Fig. 5. Kinematics for the three braking tasks (Panels A–C); kinematics and controls for the steering task (Panels D and E for bicycle and e-scooter, respectively).

3.1. Kinematics and controls

Fig. 5 shows the speed profiles from some representative trials as a participant braked gently (Panel A) and harshly (Panels B and C for planned and unplanned braking, respectively). As expected, by braking harder, the participant could stop the vehicle faster, independently of the vehicle. Fig. 5 also reports the lateral kinematics (lateral acceleration and roll rate) and handlebar control parameters (steering angle and steering angle rate) for the slalom maneuver (Panels D and E). Not surprisingly, the largest lateral kinematics happened in the slalom phase, when the handlebar movements were also more pronounced.

3.2. Braking

When braking, participants decelerated faster and achieved shorter braking distances on the bicycle than on the e-scooter. Fig. 6 shows the decelerations for the three types of braking for bicycle and e-scooter. The linear model presented in Fig. 6 (Lee et al., 2020) indicates that participants were able to stop the bike approximately twice as fast as the e-scooter (when braking harshly). Even gentle braking resulted in shorter braking times for bicycles than e-scooters (although the difference was not as large). Individual variability played a large role, especially in the gentle braking. Fig. 7 shows how the variance of the braking distance decreases when moving from gentle to harsh braking, especially for cyclists (Panel A). Response times were somewhat longer when participants rode the e-scooter than when they rode the bicycle (Panel B) and this result should be verified with a larger sample.

3.3. Steering

We modeled the steering trajectories with a sine wave as shown in Equation (1), where ω is the frequency, ϕ the phase, and α the amplitude. Fig. 8 shows the individual and averaged trajectories for the bicycle (Panel A) and e-scooter (Panel B), along with the respective models (including their parameters). The two models were similar; however, the bicycle's showed a slightly higher frequency and lower amplitude.

The e-scooter required smaller adjustments of the handlebar to slalom among the cones (Fig. 9; Panel A); however, the steering angle rate was similar across the two vehicles (Fig. 9; Panel B). The mean absolute roll rate was higher (and more variable) for the bicycle than the e-scooter (Fig. 8; Panel C), suggesting the e-scooter was more maneuverable in the slalom maneuver, possibly because the participants did not need to pedal and took advantage of the shorter wheelbase. Lateral acceleration was also higher for the bicycle (Fig. 9; Panel D). Remarkably, the variance in lateral acceleration was also greater for the bicycle. Participants started to steer earlier with the e-scooter than with the bicycle, although the variability across participants was large (Fig. 9; Panel E).

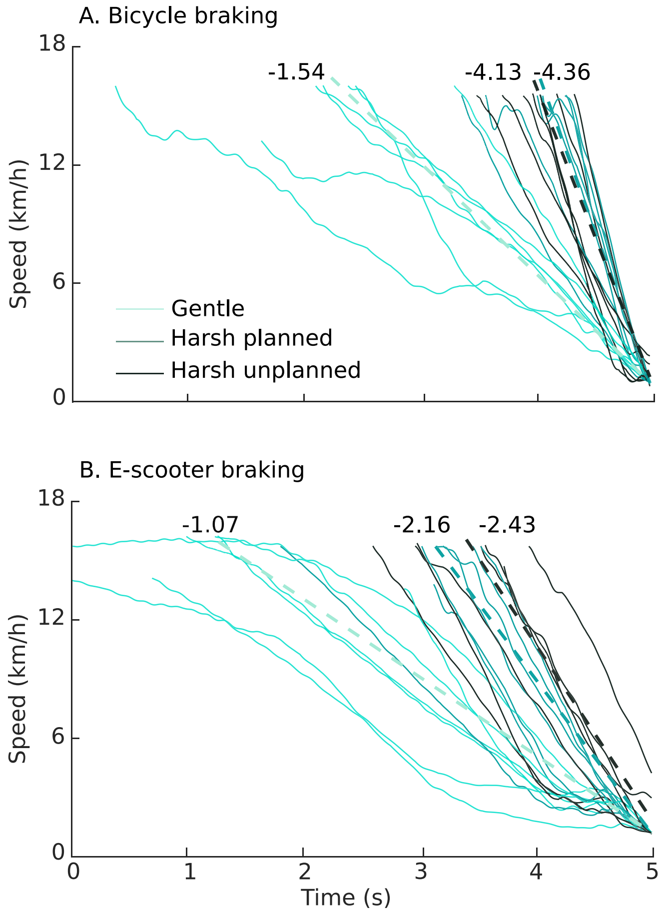

Fig. 6. Speed profiles for the braking trials. Each dashed line indicates the average braking deceleration (the associated number indicates the overall average in m/s^2) for that trial as a linear interpolation of the speed (according to Lee et al., 2020).

Finally, the delay between roll rate and steering rate was lower for the e-scooter than for the bicycle (Fig. 9; Panel F).

3.4. Subjective data

Fig. 10 shows the results from the questionnaire on a spider plot. Participants found it less comfortable to brake on the e-scooter than the bicycle, while they had the opposite experience for steering. It is worth remembering that our protocol assessed braking at high speed (17 km/h) and steering at low speed (10 km/h). Maintaining balance at low speed was reported to be equally challenging for participants on the bicycle and the e-scooter—while at high speed the bicycle was perceived as more stable than the e-scooter. The participants found the e-scooter easier to accelerate than the bicycle. Maintaining a set speed (high or low) was scored alike for the bicycle and the e-scooter. Finally, no difference in comfort level between the vehicles was perceived by the participants when mounting or dismounting.

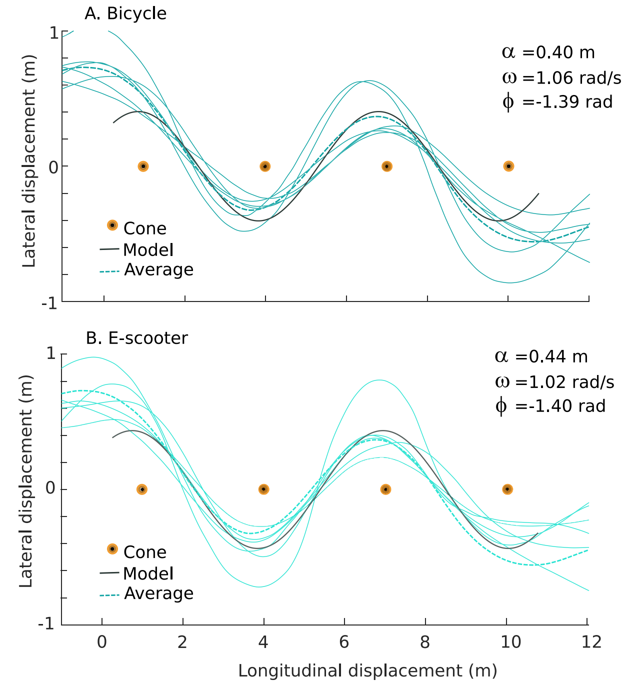

Fig. 8. Steering model for the bicycle (Panel A) and the e-scooter (Panel B), compared to individual and averaged trajectories.

4. Discussion

This paper proposes a framework to facilitate the transferability and benchmarking of research results regarding micro-mobility. We applied the framework to compare bicycles and e-scooters. In this section, we first discuss the results from our use case for braking and steering maneuvers. Then, we explain how our results may be of interest to several stakeholders, by exemplifying how data from field trials may benefit policy making, education, system design, and infrastructure design. Finally, we propose new research

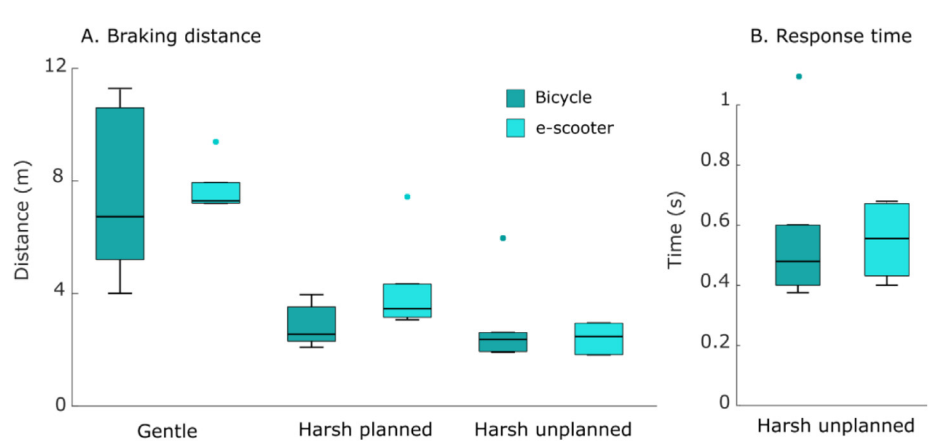

Fig. 7. Braking distance for the two vehicles in the three braking conditions (Panel A) and response time for the harsh unplanned braking (Panel B); dots indicate outliers.

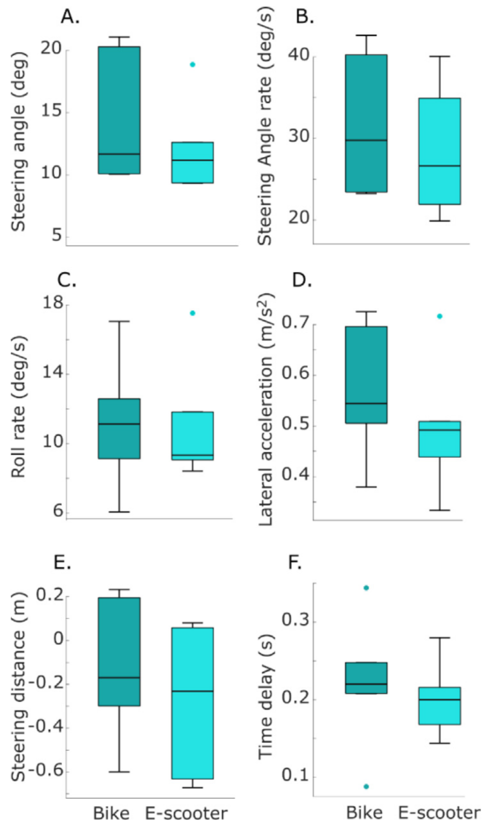

Fig. 9. Boxplots of the performance indicators for bicycle and e-scooter.

to apply and expand our framework to other micro-mobility solutions.

4.1. Braking

Overall, participants were able to brake more efficiently with the bicycle than the e-scooter; in other words, stopping a bicycle required less braking distance for both comfort and harsh braking. As expected, harsh maneuvers on the bicycle resulted in larger (approximately 3 m/s^2 higher) decelerations and shorter braking distances (approximately 4 m shorter) compared to comfortable maneuvers. The results for comfort braking are very similar to the ones reported in Lee et al. (2020), especially when the dependency between speed and braking distance is considered. Similar results were found for e-scooters: for harsh maneuvers, deceleration increased by about 1 m/s^2 and braking distance decreased by 3 m (compared to braking comfortably). The results for harsh maneuvers were consistent with those reported by Garman et al. (2020).

Unplanned, harsh braking maneuvers resulted in decelerations and braking distances similar to those in planned, harsh maneuvers, and response time was similar across the vehicles. For e-scooters, the average response time was faster than that reported in Garman et al. (2020): 0.55 s versus 1.1 s, respectively. The low variability in e-scooter braking distance (especially for comfort braking; Fig. 7) suggests that e-scooterists relied on the handbrake to slow down the e-scooter. E-scooters are also equipped with a foot brake, and jumping off the e-scooter may, in some cases, provide the best braking performance. In our study, none of the participants jumped off the e-scooter, and we did not measure the extent to which the pedal brake was used. Some experienced cyclists may be used to jumping off a bicycle to avoid a collision; however, the technique requires training and is seldom an appealing alternative for non-professional cyclists. Although it is easier to jump off an e-scooter than a bicycle, it would still require training (Faraji et al., 2020) before being successfully employed in an unexpected critical situation. Nevertheless, our study shows that e-scooters take longer (in both distance and time) to brake than bicycles, especially in critical situations when harsh braking is required. Interestingly, the results from the questionnaires confirm this finding, suggesting that riders are aware of the limited braking capacity of e-scooters compared to bicycles.

4.2. Steering

The e-scooter was easier to steer than the bicycle, possibly because of its geometry. This result was confirmed by the questionnaire data, suggesting, once more, that the riders are aware of the different trade-offs in vehicle dynamics. In the slalom maneuvers, trajectories were similar for bicycles and e-scooters (Fig. 7), although on average bicycles exhibited larger steering angles, steering-angle rates, roll angles, and lateral accelerations. In addition, the variances of these four performance indicators were larger for bicycles. E-scooters also required a shorter steering distance than bicycles. These results show that riders could steer the e-scooter more efficiently than the bicycle, possibly because of the shorter wheelbase (86 cm compared to 116 cm for the bicycle), the smaller tires (8 inches compared to 28 inches for the bicycle), and because no pedaling was required. The e-scooter's shorter wheelbase may also explain why the delay between roll rate and

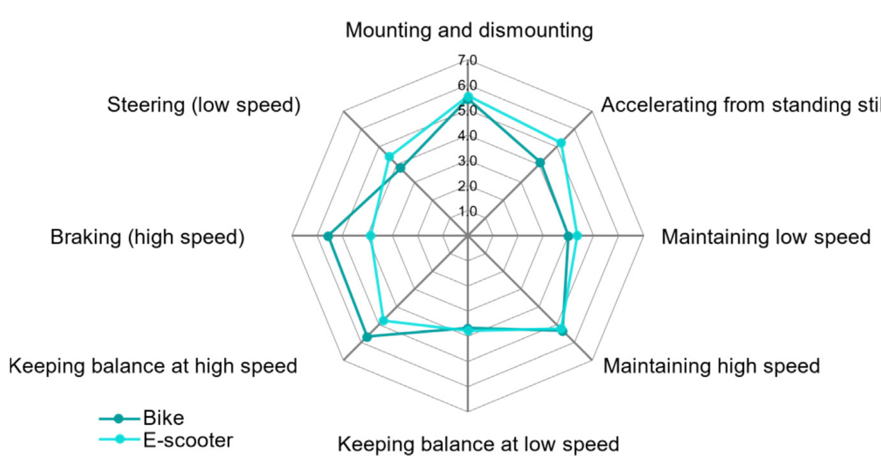

Fig. 10. Subjective data averaged over participants on a scale 1-7 (where 1 is very poor and 7 is exceptional). The diagram was created by the software from Moses (2020; https://www.github.com/NewGuy012/spider_plot, GitHub. Retrieved April 28, 2020).

steering rate was lower for e-scooters than bicycles (Fig. 8). Finally, our results are in line with Garman et al. (2020), who reported similar values for e-scooter steering angles in a slalom maneuver.

4.3. Applications

In general, our results show that e-scooters, and perhaps other micro-mobility vehicles, perform differently than traditional bicycles for braking and steering. However, some micro-mobility vehicles (e.g., e-scooters) are presently classified and regulated as bicycles in several countries (Kamphuis & Van Schagen, 2020). In our study, riders seemed to be aware of the vehicles' different braking and steering performances; however, this may not be sufficient in critical situations because users' reflexes are likely to be influenced by previous (overlearned) experience. Consequently, just as the overlearned skills from riding a bicycle do not necessarily transfer to the new vehicles, neither should bicycle regulations and classification. Future studies may leverage naturalistic data to assess the extent to which crash avoidance maneuvers in real traffic differ between e-scooters and bicycles (Dozza & Werneke, 2014). So far, our results suggest that, in the same critical situation, steering avoidance might be safer than braking for an e-scooterist, while the opposite may be true for a cyclist.

Our results also suggest that e-scooterists may negotiate urban space differently than cyclists and may be more prone than cyclists to sudden lateral displacements. This difference may influence the design of intelligent transport systems that facilitate a safe interaction with road users (Boda et al., 2018) as well as how future automated vehicles interact with cyclists and e-scooterists; consequently, models such as the ones presented in this paper may help automated vehicles anticipate the future behavior of different micro-mobility solutions and act accordingly. Our findings also suggest that perhaps geofencing should be based on road-user density; for instance, e-scooter speeds should be lower in crowded areas since e-scooterists may be prone to zigzag among other road users.

Because of the differences in maneuverability, different infrastructure may be called for to accommodate the needs of cyclists and e-scooterists. For example, a sinuous path might be safer for an e-scooterist, while a narrow path with low visibility might be less intimidating for a cyclist. While it is up to urban planning to determine the extent to which data collected following our procedure may be used for nudging (Twisk & de Hair-Buijssen, 2017) or building safer infrastructure, different micro-mobility solutions would benefit from—and possibly require—different approaches to infrastructure design. In this respect, data from sharing systems may be particularly informative for urban planning, particularly when combined with crash data and behavioral models, facilitating more sophisticated approaches to geofencing and dynamic routing. In fact, geofencing algorithms could even support real-time dynamic routing, leveraging crash risk from the combination of exposure (from GPS) and crash data (Dozza, 2017). As an example, speed limits may change dynamically, depending on the actual crash risk at a specific location, as described in Dozza, 2017; the risk can be computed in real time by comparing crash statistics with current GPS data and considering vehicle-specific performances.

Rules for e-scooters are different across different countries, even within the European Union (Kamphuis & Van Schagen, 2020). Today, several institutions are engaged in classifying micro-mobility in order to provide consistent regulation across transport modes (International Transport Forum, 2020; SAE, 2015; Styrelsen, 2020). Today's classification of micro-mobility is mainly based on *static*, objective measures such as weight or number of wheels or tracks. Field trials may complement these data with *dynamic* measures that demonstrate whether different micro-mobility vehicles behave similarly in traffic, so that future classification may take variables such as performance, maneuverability, stability, and safety into account.

Finally, results from field trials such as the one presented in this paper may inform training for new e-scooterists. Because many injuries happen on the first trip with an e-scooter (Austin Public Health, 2019), it might be that users approach an e-scooter with the same confidence as a bicycle, although they are missing the necessary skills, and possibly missing a correct mental model of the vehicle's operation. Identifying maneuvers where the difference between the vehicles' maneuverability is larger (as we did in this study) may highlight which maneuvers should be practiced by novice e-scooterists (Faraji et al., 2020).

4.4. Limitations and future studies

The selection of maneuvers and performance indicators is crucial for a fair comparison across vehicles. The more vehicles differ from each other in their geometry, the harder it is for the performance indicators to be comparable. In our example, we used indicators that are established for assessing bicycle dynamics and computed them for both bicycles and e-scooters. Therefore, we could verify our results with the previous literature on bicycles; however, our selection of performance indicators may have biased our comparison. Unfortunately, literature on e-scooters dynamics is close to absent and developing ad-hoc performance indicators for e-scooter maneuvering was beyond the scope of this work. It is worth noting that this comparison issue may affect the lateral control more than the longitudinal. In other words, the braking comparison presented in this paper is likely to be more valid than the steering comparison because braking is a less complex task than steering. The selection of maneuvers will also (inevitably) affect the comparison. In our case, we selected maneuvers that were established in the literature on cycling safety in order to ground and compare our results with the literature. Nevertheless, especially for steering, the (slalom) maneuver that we chose may not represent a standard steering avoidance maneuver, both because of the speed and the size of the cones. Future studies may expand our results and include more, and more critical, maneuvers at different speeds as proposed by Lee et al. (2020).

In this study, we tested one specific bicycle and one specific e-scooter. While the bicycle was chosen to be representative of the average urban bicycle, this aspect is much harder to control for e-scooters. In fact, since their introduction, e-scooters have been rapidly developing. For instance, the e-scooter model used in this study did not have suspension and only had an electrical and a foot brake. Nowadays, new e-scooter may have front suspensions, larger wheels, and may be equipped with mechanical brakes, like the ones on bicycles. Of course, differences in geometry and controls may severely impact the results in field trials. Interestingly, our methodology may help understand which technological improvement may lead to better safety solutions as it can compare different e-scooter models.

This study, like most similar studies (Garman et al., 2020; Kovácsová et al., 2016; Lee et al., 2020; Löcken et al., 2020), only investigated a few maneuvers, using two vehicles and only a few participants in one single country. Although the results presented in this paper are consistent with previous literature (Garman et al., 2020; Lee et al., 2020), our results should be verified on a larger number of subjects. Further, to prevent fatigue, we did not test other important maneuvers, such as comfortable steering avoidance, turning, or overtaking. Future studies may complement our results by addressing more maneuvers and more micro-mobility solutions: Segways (Zajc et al., 2018), hoverboards (Jones et al., 2016), monowheels, e-skateboards, and even the more established e-bikes (Vlakveld et al., 2015) may be legitimate candidates. Of course, these new vehicles' geometry and controls will create new challenges for instrumentation and data collection, and may require that our framework be expanded.

The framework presented in this paper has the potential to increase repeatability across studies because it promotes a systematic and objective approach for the definition of the experimental design, data analysis, and reference models from field trials. If this approach is followed in future studies, it may be easier for legislators, engineers, educators, and policymakers to compare and combine results.

Finally, although field tests provide a great opportunity for repeatability, highlighting the variability across vehicles and subjects (e.g., compare across ages; Kovácsová et al., 2016), naturalistic data will eventually be required to validate the models from field trials and eliminate any concerns about their ecological validity.

5. Conclusions

Data about kinematics and controls from micro-mobility vehicles may help safely integrate these new vehicles into urban transport. Specifically, data from field trials may inform policymakers, educators, and urban planners by objectively comparing the stability, maneuverability, and comfort of different micro-mobility solutions. To favor comparisons, studies collecting data in field trials should follow a common procedure, like the one we present in this paper, and, when possible, use similar sensors, signals, and performance indicators. The initial models for braking and steering presented in this paper may serve as references for future studies to expand the procedure presented in this paper. Our pilot experiment shows that different vehicles have different maneuvering constraints; specifically, while a bicycle may be easier to slow down, an e-scooter appears to be easier to steer. An obvious consequence for traffic safety is that the safest crash avoidance maneuver may be different for a cyclist or an e-scooterist even when the scenarios are identical. The braking and steering models presented in this paper may also support the development of intelligent systems and connected automated vehicles, by helping them predict a rider's intent to brake or steer in a critical situation. Future studies should acquire data from a larger population to verify and improve the models presented in this paper and possibly apply this procedure to a larger variety of micro-mobility vehicles. We expect future studies to show that micro-mobility vehicles such as monowheels and hoverboards have poor braking performance, especially at high speeds and in unplanned situations. The data from these studies may therefore support the development of solutions (such as training, regulations, and geofencing) that contribute to the safe integration of these vehicles into the transport system.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

6t-bureau de recherche. (2019). *Uses and users of free-floating electric scooters in France*.

Allem, J. P., & Majmundar, A. (2019). Are electric scooters promoted on social media with safety in mind? A case study on Bird's Instagram. In *Preventive medicine reports* (pp. 62–63). Elsevier Inc.. https://doi.org/10.1016/j.pmedr.2018.11.013.

Austin Public Health. (2019). *Dockless electric scooter - related injuries study*.

Badeau, A., Carman, C., Newman, M., Steenblik, J., Carlson, M., & Madsen, T. (2019). Emergency department visits for electric scooter-related injuries after introduction of an urban rental program. *American Journal of Emergency Medicine, 37*(8), 1531–1533. https://doi.org/10.1016/j.ajem.2019.05.003.

Beck, S., Barker, L., Chan, A., & Stanbridge, S. (2020). Emergency department impact following the introduction of an electric scooter sharing service. *Emergency Medicine Australasia, 32*(3), 409–415. https://doi.org/10.1111/1742-6723.13419.

Bekhit, M. N. Z., Le Fevre, J., & Bergin, C. J. (2020). Regional healthcare costs and burden of injury associated with electric scooters. *Injury, 51*(2), 271–277.

Bird. (2019). *A look at e-scooter safety*.

Bjerkan, A. M., Engebretsen, A., & Steinbakk, R. T. (2020). *Skader på sykkel og elektrisk sparkesykkel i Oslo*.

Blomberg, S. N. F., Rosenkrantz, O. C. M., Lippert, F., & Christensen, H. C. (2019). Injury from electric scooters in Copenhagen: a retrospective cohort study. *BMJ open, 9*(12) e033988.

Boda, C.-N., Dozza, M., Bohman, K., Thalya, P., Larsson, A., & Lubbe, N. (2018). Modelling how drivers respond to a bicyclist crossing their path at an intersection: How do test track and driving simulator compare? *Accident Analysis and Prevention, 111*. https://doi.org/10.1016/j.aap.2017.11.032.

Boda, C.-N., Lehtonen, E., & Dozza, M. (2020). A computational driver model to predict driver control at unsignalised intersections. *IEEE Access, 8*, 104619–104631.

Brännström, M., Coelingh, E., & Sjöberg, J. (2014). Decision-making on when to brake and when to steer to avoid a collision. *International Journal of Vehicle Safety 1, 7*(1), 87–106.

Buczyński, A., & Fahrenkrug, E. (2020). *Integrate EuroVelo, the European cycle route network, into the TEN-T*.

Chang, A. Y. J., Miranda-Moreno, L., Clewlow, R., & Sun, L. (2019). *Trend or fad? Deciphering the enablers of micromobility in the US*. SAE International.

Dingus, T. A., Neale, V. L., Klauer, S. G., Petersen, A. D., & Carroll, R. J. (2006). The development of a naturalistic data collection system to perform critical incident analysis: An investigation of safety and fatigue issues in long-haul trucking. *Accid Anal Prev*, *38*(6), 1127–1136. https://doi.org/S0001-4575(06)00077-7 [pii] 10.1016/j.aap.2006.05.001

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*, 83–91.

Dozza, M. (2013). What is the relation between bicycle dynamics and safety in the real World? *Proceedings, bicycle and motorcycle dynamics 2013, symposium on the dynamics and control of single track vehicles, 11–13 November 2013, Narashino, Japan*.

Dozza, M., & Fernandez, A. (2013). Understanding bicycle dynamics and cyclist behavior from naturalistic field data. *Ieee transactions on intelligent transportation systems*.

Dozza, M. (2017). Crash risk: How cycling flow can help explain crash data. *Accident Analysis and Prevention, 105*, 21–29.

Faraji, F., Lee, J. H., Faraji, F., MacDonald, B., Oviedo, P., Stuart, E., ... Gosman, A. A. (2020). Electric scooter craniofacial trauma. *Laryngoscope Investigative Otolaryngology, 5*(3), 390–395.

Fearnley, N., Berge, S. H., & Johnsson, E. (2020). Delte elsparkesykler i Oslo. *Retrieved from Oslo:* https://www.toi.no/getfile.php?mmfileid=52254.

Garman, C., Como, S. G., Campbell, I. C., Wishart, J., O'Brien, K., & McLean, S. (2020). Micro-mobility vehicle dynamics and rider kinematics during electric scooter riding. *SAE Technical Papers*. https://doi.org/10.4271/2020-01-0935.

Gehlert, T., Kuhn, M., Schleinitz, K., Petzoldt, T., Schwanitz, S., & Gerike, R. (2012). The german pedelec naturalistic cycling study - study design and first experiences. *Proceedings of the first International Conference on Cycling Safety, Helmond, 7-9 November 2012*.

Genta, G., & Morello, L. (2009). *The automotive chassis*. Springer.

Gössling, S. (2020). Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. *Transportation Research Part D: Transport and Environment, 79* 102230.

Hatfield, J., Dozza, M., Patton, D. A., Maharaj, P., Boufous, S., & Eveston, T. (2017). On the use of naturalistic methods to examine safety-relevant behaviours amongst children and evaluate a cycling education program. *Accident Analysis and Prevention*. https://doi.org/10.1016/j.aap.2017.08.025.

Haworth, N. L., & Schramm, A. (2019). Illegal and risky riding of electric scooters in Brisbane. *Medical Journal of Australia, 211*(9), 412–413.

Hitchings, J., Weekley, J., & Beard, G. (2019). *Review of current practice and safety implications of electric personal mobility devices*.

Huertas-Leyva, P., Dozza, M., & Baldanzini, N. (2018). Investigating cycling kinematics and braking maneuvers in the real world: E-bikes make cyclists move faster, brake harder, and experience new conflicts. *Transportation Research Part F: Traffic Psychology and Behaviour.*. https://doi.org/10.1016/j.trf.2018.02.008.

International Transport Forum. (2020). *Safe Micromobility*.

Ishmael, C. R., Hsiue, P. P., Zoller, S. D., Wang, P., Hori, K. R., Gatto, J. D., . . ., Bernthal, N. M. (2020). An early look at operative orthopaedic injuries associated with electric scooter accidents: bringing high-energy trauma to a wider audience. *JBJS*, *102*(5), e18–e18.

Jones, S., Khandekar, S., Siraj, F., Talaseela, B., Mohammed, M. A., & Kamhawy, A. (2016). Hoverboards and upper limb fractures in children. *Acta Orthopædica Belgica, 82*, 896–900.

Kamphuis, K., & Van Schagen, I. (2020). *E-scooters in Europe: Legal status, usage and safety: results of a survey in FERSI countries*.

Kovácsová, N., de Winter, J. C. F., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. *Transportation Research Part F: Traffic Psychology and Behaviour, 42*, 28–43. https://doi.org/10.1016/j.trf.2016.06.018.

Lee, O., Rasch, A., Schwab, A. L., & Dozza, M. (2020). Modelling cyclists' comfort zones from obstacle avoidance manoeuvres. *Accident Analysis & Prevention, 144* 105609.

Liew, Y. K., Wee, C. P. J., & Pek, J. H. (2020). New peril on our roads: A retrospective study of electric scooter-related injuries. *Singapore Medical Journal, 61*(2), 92.

Llorca, C., Angel-Domenech, A., Agustin-Gomez, F., Ferrer, V., & Garcia, A. (2014). Motor vehicles overtaking cyclists on two-lane rural roads: Analysis on speed and lateral clearance. *International cycling safety conference 2014*.

Löcken, A., Brunner, P., & Kates, R. (2020). Impact of hand signals on safety: two controlled studies with novice e-scooter riders. In *12th international conference on automotive user interfaces and interactive vehicular applications* (pp. 132–140).

Moftakhar, T., Wanzel, M., Vojcsik, A., Kralinger, F., Mousavi, M., Hajdu, S., ... Starlinger, J. (2020). Incidence and severity of electric scooter related injuries after introduction of an urban rental programme in Vienna: A retrospective multicentre study. *Archives of Orthopaedic and Trauma Surgery*, 1–7.

Møller, T. H., & Simlett, J. (2020). Micromobility: Moving cities into a sustainable future. *EY*.

Morando, A., Victor, T., & Dozza, M. (2019). A reference model for driver attention in automation: Glance behavior changes during lateral and longitudinal assistance. *IEEE Transactions on Intelligent Transportation Systems, 20*(8). https://doi.org/10.1109/TITS.2018.2870909.

Namiri, N., Lui, H., Tangney, T., Allen, I., Cohen, A., & Breyer, B. (2020). Electric scooter injuries and hospital admissions in the United States, 2014–2018. *JAMA Surgery, 155*. https://doi.org/10.1001/jamasurg.2019.5423.

O'Hern, S., & Estgfaeller, N. (2020). A scientometric review of powered micromobility. *Sustainability, 12*(22), 9505.

Portland Bureau of Transportation. (2018). *2018 E-SCOOTER PILOT User Survey Results*.

Ramboll (2020). *Achieving sustainable micro-mobility*. Ramboll.

Rasch, A., & Dozza, M. (2020). Modeling drivers' strategy when overtaking cyclists in the presence of oncoming traffic. *IEEE transactions on intelligent transportation systems*.

Rasch, A., Dozza, M., & Håland, Y. (2016). *Evaluation of a new narrow and tiltable electric tricycle (e-trike) concept*.

Rasch, A., Panero, G., Boda, C.-N., & Dozza, M. (2020). How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data. *Accident Analysis & Prevention, 139* 105494.

Rauch, H. E., Tung, F., & Striebel, C. T. (1965). Maximum likelihood estimates of linear dynamic systems. *AIAA Journal, 3*(8), 1445–1450.

Sae (2015). *Operational definitions of driving performance measures and statistics*. PA: Society of Automotive Engineers Warrendale.

SAE Committee, S. and D. M. (2018). Taxonomy and definitions for terms related to shared mobility and enabling technologies. SAE International.

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.

Schwab, A. L., & Meijaard, J. P. (2013). A review on bicycle dynamics and rider control. *Vehicle System Dynamics, 51*(7), 1059–1090. https://doi.org/10.1080/00423114.2013.793365.

Sharkey, M., Ahrens, P., Munk, S., & Bogdanowicz, T. (2020). *Micromobility and active travel in the UK: The rise of smaller modes, and resulting infrastructure, safety and regulation implications*.

Stigson, H, Malakuti, I., & Klingegård, M. (2020). *Electric scooters injuries and causes: Analysis of Swedish accident data*.

Stigson, Helena, & Klingegård, M. (2020). *Kartläggning av olyckor med elsparkcyklar och hur olyckorna kan förhindras*.

Stockholms Stad. (2019). *Olycksanalys Elsparkcyklar i Stockholms stad*.

Transportstyrelsen (2020). *Utredning behov av förenklade regler för eldrivna enpersonsfordon - delrapport 1*.

Trafikkontoret, G. S. (2009). *HISTORIK, KUNSKAP OCH ANALYS FÖR TRAFIKSÄKERHETSPROGRAM 2010–2020, Kap. 8.2 Cyklister*.

Trivedi, B., Kesterke, M. J., Bhattacharjee, R., Weber, W., Mynar, K., & Reddy, L. V. (2019). Craniofacial injuries seen with the introduction of bicycle-share electric scooters in an urban setting. *Journal of Oral and Maxillofacial Surgery, 77*(11), 2292–2297.

Trivedi, T. K., Liu, C., Antonio, A. L. M., Wheaton, N., Kreger, V., Yap, A., . . . Elmore, J. G. (2019). Injuries associated with standing electric scooter use. *JAMA Network Open, 2*(1), e187381.

Twisk, D., & de Hair-Buijssen, S. (2017). *MeBeSafe: Infrastructure & car based nudges to improve cyclist safety*.

Twisk, D., Stelling, A., Van Gent, P., De Groot, J., & Vlakveld, W. (2021). Speed characteristics of speed pedelecs, pedelecs and conventional bicycles in naturalistic urban and rural traffic conditions. *Accident Analysis & Prevention, 150* 105940.

Vernon, N., Maddu, K., Hanna, T. N., Chahine, A., Leonard, C. E., & Johnson, J.-O. (2020). Emergency department visits resulting from electric scooter use in a major southeast metropolitan area. *Emergency Radiology, 27*(5), 469–475.

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 traffic situations: A field experiment. *Accident Analysis & Prevention, 74*, 97–106. https://doi.org/10.1016/j.aap.2014.10.018.

Westerhuis, F., & De Waard, D. (2016). Using commercial GPS action cameras for gathering naturalistic cycling data. *Journal of the Society of Instrument and Control Engineers, 55*(5), 422–430.

Wüster, J., Voß, J., Koerdt, S., Beck-Broichsitter, B., Kreutzer, K., Märdian, . . . Doll, C. (2020). Impact of the rising number of rentable e-scooter accidents on emergency care in Berlin 6 months after the introduction: A maxillofacial perspective. *Craniomaxillofacial Trauma & Reconstruction*, 1943387520940180–1943387520940180.

Zagorskas, J., & Burinskienė, M. (2020). Challenges caused by increased use of e-powered personal mobility vehicles in European cities. *Sustainability, 12*(1), 273.

Zajc, A., Spielhaupter, A., AB, K. & P., & Eriksson, J. (2018). *Eldrivna enpersonsfordon – En kunskapsöversikt om deras plats i trafiken*.

Marco Dozza received the Ph.D. degree in bioengineering from the University of Bologna, Italy, in collaboration with Oregon Health & Science University, Portland, OR, USA, in 2007. After graduation, he worked as a System Developer with Volvo Technology, for over two years, a research and innovation company inside the Volvo group. Since 2009, he has been with the Chalmers University of Technology, Gothenburg, Sweden, where he is currently a Professor and leads the Crash Analysis and Prevention Unit. He is an Examiner for the course Active Safety in the Master's Programme for Automotive Engineering. He is working with SAFER, the Vehicle and Traffic Safety Center at Chalmers.

Alessio Violin received the B.Sc. degree in mechanical engineering from Politecnico di Milano, Milan, Italy in 2018, and the M.Sc. degree in automotive engineering from Politecnico di Torino, Turin, Italy in 2020. During his master degree, Alessio spent the last year at Chalmers University of Technology where he is currently working as a project assistant at the Crash Analysis and Prevention Unit, taking part to the European project L3Pilot. Goal of the project is to evaluate the viability of autonomous driving as a safe and efficient means of transportation.

Alexander Rasch received the B.Sc. degree in mechanical engineering from RWTH Aachen University, Aachen, Germany, in 2016, and the M.Sc. degree in systems, control and mechatronics from the Chalmers University of Technology, Gothenburg, Sweden, in 2018, where he is currently pursuing the Ph.D. degree, on computational models for driver behavior in interaction with pedestrians and cyclists, mainly in overtaking scenarios. The goal of his research is to develop driver models that can improve advanced driver assistance systems.