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How do different micro-mobility vehicles affect longitudinal control? Results from a field experiment

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A B S T R A C T

Introduction: While micromobility vehicles offer new transport opportunities and may decrease fuel emissions, the extent to which these benefits outweigh the safety costs is still uncertain. For instance, e-scooterists have been reported to experience a tenfold crash risk compared to ordinary cyclists. Today, we still do not know whether the real safety problem is the vehicle, the human, or the infrastructure. In other words, the new vehicles may not necessarily be unsafe; the behavior of their riders, in combination with an infrastructure that was not designed to accommodate micromobility, may be the real issue. *Method:* In this paper, we compared e-scooters and Segways with bicycles in field trials to determine whether these new vehicles create different constraints for longitudinal control (e.g., in braking avoidance maneuvers). *Results:* The results show that acceleration and deceleration performance changes across vehicles; specifically, e-scooters and Segways that we tested cannot brake as efficiently as bicycles. Further, bicycles are experienced as more stable, maneuverable, and safe than Segways and e-scooters. We also derived kinematic models for acceleration and braking that can be used to predict rider trajectories in active safety systems. *Practical Applications:* The results from this study suggest that, while new micromobility solutions may not be intrinsically unsafe, they may require some behavior and/or infrastructure adaptations to improve their safety. We also discuss how policy making, safety system design, and traffic education may use our results to support the safe integration of micromobility into the transport system.

1. Introduction

New micromobility vehicles (SAE Committee, 2018), compact and electrically powered, are on the rise worldwide (6t-bureau de recherche, 2019; Chang et al., 2019; Fitt & Curl, 2020; O'Hern & Estgfaeller, 2020; Portland Bureau of Transportation, 2018). A few years ago, e-bicycles (i.e., assisted cycles, pedelecs [SAE Committee, 2018]) were a new transport phenomenon that created some concerns in the safety research community (Huertas-Leyva et al., 2018; MacArthur et al., 2014; Schleinitz et al., 2017; Twisk et al., 2021). Today, e-bicycles are conventional, while new micromobility (e-)vehicles with different geometries, number of wheels, and number of tracks present new challenges for the transport system (Abduljabbar et al., 2021; O'Hern & Estgfaeller, 2020). While monowheels, e-skates, and Segways are not very popular yet and, maybe, they will never be, e-scooters are; they outnumber e-bicycles in many urban centers. It is hard not to see a trend toward electrical vehicles, and it is not a given that e-scooters are the peak of this transformation. In any case, micromobility is here to stay (Gössling, 2020), and it may indeed solve some congestion and pollution issues (6t-bureau de recherche, 2019; Abduljabbar et al., 2021; Portland Bureau of Transportation, 2018; Sharkey et al., 2020). Unfortunately, the safety toll that new micromobility vehicles—and e-scooters specifically—take may be hard to mitigate (Santacreu et al., 2020).

Several studies have shown that riding e-scooters is unsafe: the crash risk is 10 times higher than riding a bicycle (Fearnley et al., 2020). E-scooters also cause major injuries (Badeau et al., 2019; Bekhit et al., 2020; Ishmael et al., 2020; Namiri et al., 2020) that are different from the ones experienced by (e-)cyclists (Beck et al., 2020; Cicchino et al., 2021; B. Trivedi et al., 2019; T. K. Trivedi et al., 2019; Wüster et al., 2020). Several factors may contribute to explain these injury variations, including the different demographics and attitudes in wearing helmets between the cyclist and e-scooterist population. However, some differences (e.g., the higher prevalence of lower extremity injuries for e-scooterists compared to cyclists; Cicchino et al., 2021) suggest that the vehicle geometry and control also play a role.

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Today, we know very little about the causes of e-scooter crashes. The vehicles often take the blame, although road-user behavior and infrastructure may play more important roles in crash causation. Most of the research on e-scooter safety makes use of data collected after the crash has happened, either by the police, hospitals, or insurance companies (Stigson et al., 2020). While these data describe the consequence of a crash, they do not show what happened just before the crash; in other words, they may not show what caused the crash. Data collected in the field, on the other hand, either naturalistically (Dozza & Werneke, 2014) or in controlled experiments (Kovácsová et al., 2016), may complement the crash data collected a posteriori and help us understand why micromobility crashes occur—and how to avoid them (Dozza et al., 2022).

The same data may help educate micromobility riders; after all, 33 % of the injuries happen during the very first trip of novice riders (Austin Public Health, 2019), suggesting that the crash was caused by the riders' inexperience. In addition, field data may contribute to the development of active safety systems, such as emergency braking, which need to predict the rider behavior in order to provide timely and acceptable interventions (Boda et al., 2018). Finally, today's policy making, in the form of bans or geo-fencing, responds to general and static requirements, rather than dynamically changing in time and space according to the actual crash risk at a given moment. However, geo-fencing may have this ability if a sufficiently large amount of field data are available.

In this paper, we follow the procedure proposed by Dozza et al. (2022) for field data collection and analysis, and compare longitudinal control (i.e., acceleration and braking) among e-scooters, Segways, and bicycles (with and without assisted pedaling). Our main hypotheses were that: (1) as urgency increases, riders may be able to achieve larger acceleration and decelerations with all vehicles; (2) not all vehicles may exhibit the same acceleration and braking performance; and (3) braking and acceleration trajectories may be accurately predicted with simple linear models for all micromobility vehicles. By modeling micromobility kinematics, we can improve the threat assessment of active safety systems and promote a better understanding of how new micromobility vehicles differ from bicycles from a safety point of view.

2. Methods

The data collection and analyses in this study adapted the procedure from Dozza et al. (2022) by comparing acceleration (in addition to braking) and including a Segway (in addition to bicycles and e-scooters).

2.1. Participants

Nine female and 25 male subjects participated to this experiment by maneuvering an e-scooter, a Segway, and a bicycle in field trials. The participants' mean age (±standard deviation) was 23.5 y ± 4.2, mean height (±standard deviation) 1.75 m ± 0.08, and mean weight (±standard deviation) 71.5 kg ± 9.5. Participants shorter than 160 cm or heavier than 85 kg were excluded from the study to comply with the suggested heights and weights from the vehicle manufacturers. The inclusion criteria made sure that participants could ride a bicycle, were between 18 and 50 years old, had no disabilities, and had never been in a severe road crash. These criteria were set to control for possible biases in the results as indicated in (Dozza et al., 2022). Participants who had any symptoms of COVID-19 in the two weeks prior to the experiment were not allowed to take part. The maneuvers required the participant to longitudinally control (e.g., accelerate and brake) the vehicles in different conditions. Each subject signed a consent form before the experiment. The study was approved by the Swedish Ethical Review Authority (Etikprövningsmyndigheten; Ref. 2019–04547). An ad-hoc health insurance covered the participants during the experiment.

2.2. Equipment

The e-scooter (Ninebot ES2), Segway (Ninebot S), and bicycle (Monark Karin 3-VXL) were equipped with a logger and sensors for the collection of vehicle kinematics (Fig. 1). Specifically, the logger was based on a Raspberry Pi 3 model B, and kinematics were collected with an inertial measurement unit (IMU: PhidgetSpatial 3/3/3 1044_B). In addition, a light detection and ranging sensor (LiDAR: HOKUYO UXM 30LAH EWA), installed on the proving ground, was used to track the vehicles during the experiment. The data from the IMU and the LiDAR were combined to achieve a more accurate estimation of the vehicle kinematics than either sensor alone could provide. In particular, the longitudinal acceleration from the IMU and the trace of the centroid of the vehicles from the LiDAR were combined to estimate the position and speed of the rider during each maneuver. A Rauch-Tung-Striebel smoother made this combination possible (Rauch et al., 1965). More details about the processing are presented in the work by Billstein and Svernlöv (2021).

2.3. Protocol

After a period of training so the participants could get acquainted with the vehicles' operation, all participants were asked to accelerate and brake the three vehicles in five different tasks.[1] Two acceleration tasks required the participants to bring the vehicle to a constant speed of 17–20 km/h from a standstill either comfortably (comfort task) or harshly (harsh task). There were three braking tasks that all required braking from a constant 17–20 km/h speed. In the comfort braking task, they were asked to brake comfortably. In the harsh planned task, the participant was supposed to brake as late and hard as possible, stopping just before a line on the ground. In the unexpected task, the experimenter gave a command to stop at a random time and the participant was asked to respond by braking as hard as possible. These different braking conditions were chosen to simulate planned and unplanned braking maneuvers (Huertas-Leyva et al., 2018, 2019); the difference between them would help identify the role of expectation on response time (Dozza et al., 2022). The order of the vehicles and tasks was randomized for each subject, but all trials were completed for each of the vehicles before a new vehicle was ridden. The experimental conditions are shown on Fig. 2. The bicycle was used both as an e-bicycle and a conventional bicycle; in other words, each participant performed the experiment on the bicycle twice, with and without electrical assistance. Therefore, although only three vehicles were tested in this study, we present results for four different riding conditions: the e-scooter, the Segway, and the two bicycle configurations (assisted and unassisted).

2.4. Subjective data

After completing the tasks, the participants were asked to fill in a questionnaire that assessed: (1) how much previous experience they had with the different vehicles in the experiment and (2) their opinions of the performance of the vehicles during the experiment. For this second part, taken from works by (Dozza et al., 2022; Rasch et al., 2016), the participants ranked the four vehicles on a 7-level Likert scale (from 1 = Very poor, to 7 = Exceptional). The following riding six categories were ranked: mounting and dismount-

[1] https://www.youtube.com/watch?v=FWWfsQrtDQY.

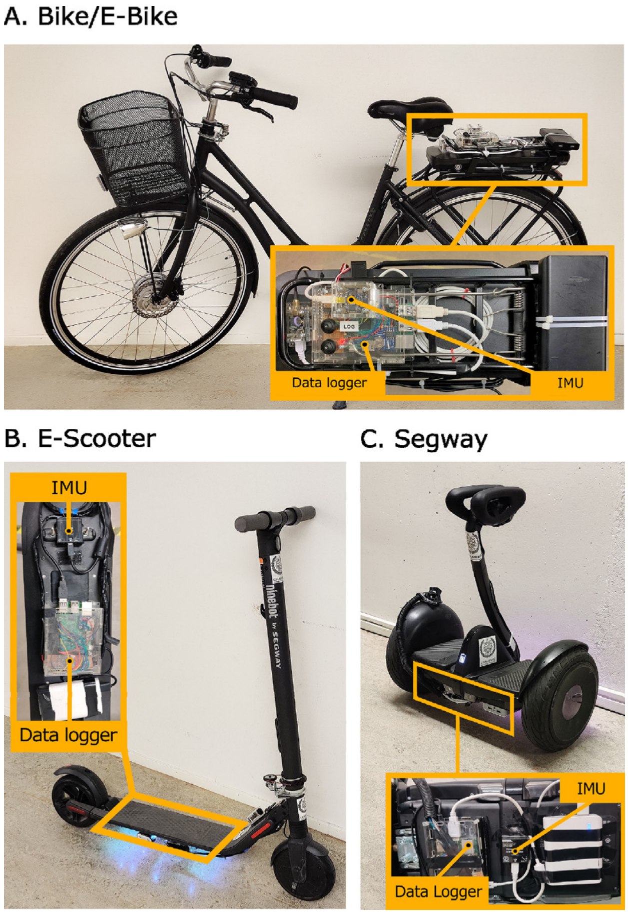

Fig. 1. Instrumented vehicles with data loggers and inertial measurement units (IMUs).

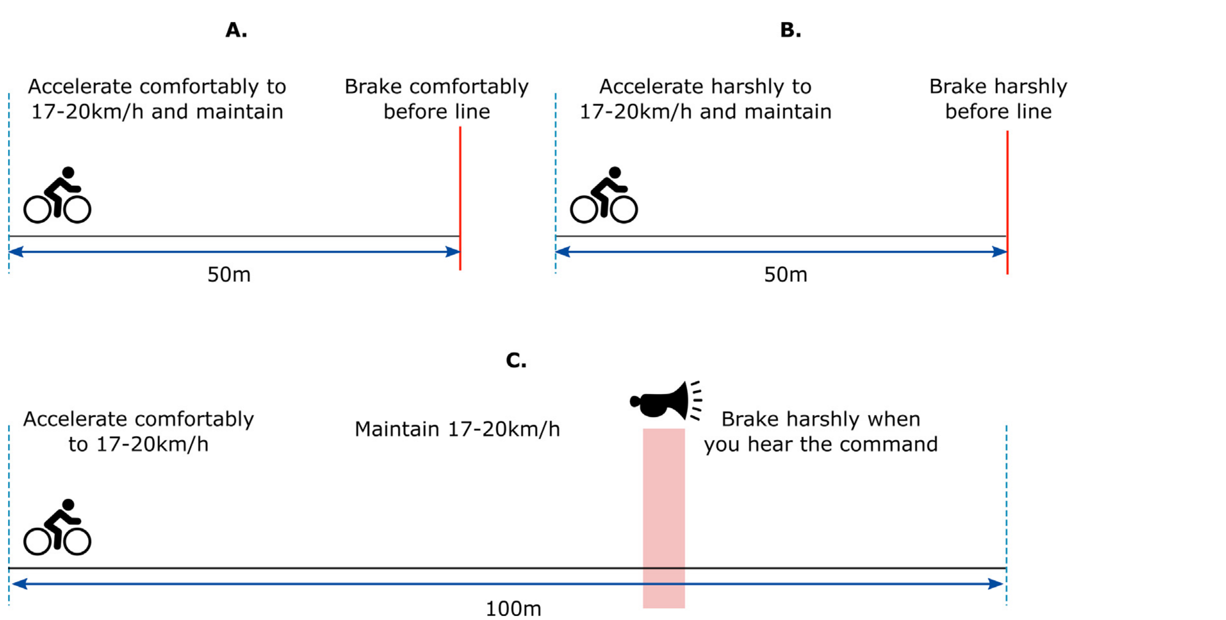

Fig. 2. Experimental protocol. Panel A: accelerating and braking comfortably. Panel B: accelerating and braking harshly. Panel C: braking harshly in response to a command from the experimenter; in this condition the ridden distance was larger than in the other conditions (100 m vs 50 m) to increase the variability of the braking command time.

ing, maintaining balance at low speed, maintaining balance at high speed, braking at low speed, braking at high speed, and accelerating from a standstill. The following four categories were ranked: stability, maneuverability, comfort, and safety.

2.5. Analyses

The accelerations and decelerations in the five tasks were modeled with linear regressions similar to those in previous studies (Kovácsová et al., 2016; Lee et al., 2020). We also computed the coefficient R^2 to verify the goodness of fit of the linear models. For the braking maneuvers, the distance covered to achieve a full stop was also computed. In addition, we compared the difference between the marked line and the actual position where the participants stopped, to determine how accurately they could estimate their braking distance. Finally, we computed the response time (i.e., the time passed between when the experimenter issued the stop command and when the vehicle started decelerating) for the unexpected braking task, to establish whether the vehicle type affected braking response time (Huertas-Leyva et al., 2018, 2019). The braking maneuver was defined as beginning when the vehicle speed dropped below 16 km/h (12 km/h for the Segway) and ending when it dropped below 2.5 km/h. The acceleration maneuver was defined to begin when the vehicle speed exceeded 2.5 km/h and end when it exceeded 16 km/h (12 km/h for the Segway). The reaction time in the unexpected-braking maneuver was defined to begin when the experimenter gave the stop command and end when the speed had dropped by 1 km/h.

Several generalized linear mixed-effect models (including the participant ID as a random effect and gender, vehicle, and maneuver type as fixed factors) were created to verify the significance of the results. Post-hoc tests were run on the results of the model whenever a factor with more than two categories was significant. The threshold for statistical significance was set to $\alpha = 0.05$ and adjusted with the Bonferroni correction to control for multiple tests across different analyses with uncorrelated measures. (All statistical analyses used the Statistics and Machine Learning Toolbox in Matlab and specifically the functions *fitglme* and *coefTest*.).

3. Results

3.1. Dataset

Although we recruited 34 participants, only 25 of them felt comfortable riding the Segway and only 14 out of these 25 provided reliable sensor data for modeling acceleration and braking. Therefore, while the comparisons across the bicycle, e-bicycle, and e-scooter use the same population, the data for the Segway only include a subset of the population (significantly smaller for the kinematics analysis and slightly smaller for the questionnaire analysis). We also experienced other minor data losses. For instance, one of the participants crashed during the experiment; it was then stopped and none of the data were used for the analysis. Data were also excluded from the analysis when the participant did not reach the desired speed before starting braking. It is worth noting that we experienced a significant data loss for technical issues only on the Segway. This was mainly the consequence of a malfunctioning USB drive in the Segway installation.

All participants were very used to riding a conventional bicycle and much less experienced riding with the other vehicles (Table 1). An issue with the Segway was winning the fear of falling when stepping on the vehicle, which is necessary to start riding. In fact, to ride the Segway, the participants had to step with both feet on the vehicle within a short time and balance longitudinally. This action may be uncomfortable (even for experienced riders) because it creates some forward and backward sway that may feel like losing equilibrium. Nine participants did not win, or did not want to try to win, this fear of falling and just refused to ride the Segway; however, most of the data loss was the consequence of technical issues. In the training phase, participants could practice with any vehicle as long as they wanted and, on average, this training phase took 15 min per participant.

3.2. Acceleration maneuvers

Fig. 3 shows the average acceleration across all subjects for comfort and harsh acceleration maneuvers. It can be observed that the assisted bicycle enabled greater accelerations (up to 20 km/h) than the other vehicles; further, the Segway stopped accelerating as it approached 15 km/h, possibly because its design felt unstable at higher speed, so people backed off. Table 1 reports the angular coefficients from the regression models, representing the average acceleration during the trials. Harsh maneuvers resulted in statistically significantly larger accelerations than comfort maneuvers ($t = 7.5$; $p \ll 0.01$; Appendix Table A), suggesting that the participants understood the instructions and could control the vehicles accordingly. While accelerations were not statistically significantly different across gender or age, they were different across vehicles ($F = 16.4$; $p \ll 0.001$; Appendix Table A). Specifically, the assisted bicycle accelerated significantly faster than the e-scooter or the conventional bicycle. The acceleration of the Segway was also very high in the beginning of the maneuver. (Table 2 shows the average acceleration of the Segway until it reached 12 km/h, which may not be directly comparable with that of the other vehicles, which were able to reach 17–20 km/h as instructed.).

3.3. Braking maneuvers

The average speeds over time for each of the three braking maneuvers are presented in Fig. 4. Table 3 complements Fig. 4 by presenting the linear coefficients from the regression models for all vehicles and braking maneuvers. In all maneuvers, the Segway achieved a lower deceleration compared to the other vehicles and the deceleration started at a lower speed. It is very important to keep these differences in mind, especially when comparing the Segway's braking distances with those of the other vehicles.

When riding the bicycle (in both assisted and unassisted modes), the participants were able to brake with larger decelerations than when riding the other vehicles, and this result was statistically significant ($F = 39$; $p \ll 0.001$; Appendix Table B1). The participants' braking performance when riding the Segway was poorer (i.e., deceleration was lower) than for the other vehicles. As expected, the two harsh braking maneuvers resulted in statistically significantly larger braking decelerations for all vehicles ($F = 8.87$; $p \ll 0.001$). What was somewhat surprising is that the unexpected harsh braking task resulted in slightly greater decelerations than the planned harsh braking. No statistically significant difference in braking deceleration was found across ages or genders (Appendix Table B1).

While the braking distances were similar for the assisted and unassisted bicycle modes, the braking distance was statistically significantly longer for the e-scooter than for the bicycle in the harsh braking conditions (Fig. 5; Appendix Table B2-B4). The braking distance was also shorter for Segways than for e-scooters. However, this is not a valid comparison, as participants on the Segway were only able to reach 15 km/h (despite the Segway design allowing for higher speeds), and therefore the shorter distance is likely a consequence of the lower speed (Fig. 5). No statistically significant effect of gender or age was found on the braking distance (Appendix Table B2-B4). The response times were not only similar across gender and age, but also across all vehicles—with the exception of the e-scooter, which induced statistically significantly larger response times (Fig. 6; $F = 6.7$; $p \ll 0.01$; Appendix Table B5). Further, during the harsh (planned) braking task, participants riding the e-scooter crossed the stop line marked on the ground 61% of the time, while this line was exceeded only 18% and 14% of the time for the assisted and unassisted bicycle, respectively. Finally, while they were riding the Segway, they crossed the line in 71% of the trials.

3.4. Subjective data

Table 4 shows some of the results from the questionnaire probing the participants' opinions of the vehicles' performance in different situations. The electrified vehicles, possibly because they required less physical effort, were perceived as more comfortable than the unassisted bicycle when accelerating from a standstill (this result was statistically significant; Appendix Table S1-S6). The assisted and unassisted bicycle tasks were scored similarly in all other situations. The Segway scored statistically significantly lower than the other vehicles for mounting and dismounting, maintaining balance at high speed, and braking at high speed (Appendix Table S1-S6). While all vehicles were similarly rated by the participants at low speed, the e-scooter and the Segway were perceived as less stable as speed increased (both for simply balancing and for braking). Gender did not statistically significantly influence any of the categories in Table 4 (Appendix Table S1-S6). However, age did: the older the subject, the lower the ratings (Appendix Table S1-S6). Nevertheless, the effect of age was small compared to the effect of vehicle type (Appendix Table S1-S6).

The Segway also scored lower than the other vehicles for overall stability, maneuverability, comfort, and safety (Table 4); these differences, too, were statistically significant (Appendix Table S7-S10). The e-scooter was also perceived as less stable and safe than the assisted and unassisted bicycle; however, this result was on the border for statistical significance. The effect of gender was not statistically significant for comfort, stability, maneuverability, or safety, but the effect of age was (Appendix Table S7-S10). Specifically, the older the subject, the less comfortable, stable, maneuver-

Table 1
Experience of the participants with riding vehicles. (For the Segway, we reported the data only from the 25 subjects that contributed to the questionnaire analysis.).

	Bike	e-bike	e-scooter	Segway
Never	2	27	12	24
Few days per year	7	4	7	0
Few days per month	8	2	8	1
Few days per week	9	1	4	0
Everyday	8	0	3	0

able, and safe the vehicle ranking. (Notably, these effects were most pronounced for the safety category and for the Segway.) Table 5 reports the correlation matrix for the four categories presented at the bottom of Table 4; it may be observed that the correlation was high among all categories, particularly between safety and stability.

4. Discussion

In this study, we applied the procedure for data collection and analysis from Dozza et al.'s (2022) field study to the comparison of the longitudinal control of a bicycle (with and without assisted pedaling), an e-scooter, and a Segway. Our results show that, indeed, the same participant may demonstrate different acceleration and braking performance depending on the vehicle. Nevertheless, we also verified that, independently of the vehicle and of the emergency of the maneuver, riders braked with a constant deceleration (this is evident from the very large R^2 coefficients in all models; see Tables 2 and 3). This finding, in line with previous work on bicycle dynamics (Lee et al., 2020), is important for the application of our models to active safety: the linear coefficients from our regression analysis can accurately predict micro-mobility kinematics—specifically, stopping distance. In other words, an (automated) vehicle using our models may estimate whether a rider approaching an intersection is still able to brake and stop in time to avoid a collision and, once the rider starts braking, what the trajectory is going to be (Boda et al., 2020). The data collected from the comfort maneuvers in our experiment may provide a lower bound for these predictions for the threat assessment of an active safety system, and the harsh maneuvers may estimate a higher bound. Further, this paper shows that vehicle classification is essential for an accurate prediction, because the braking and acceleration performances vary largely across the micromobility vehicles tested.

Riders could accelerate almost twice as fast and brake twice as hard when they compromised comfort for urgency (i.e., comfort vs harsh conditions). While this is the first study, to our knowledge, presenting acceleration data from micromobility vehicles, previous studies assessed braking performance. In particular, Dozza et al. (2022) presented results from six cyclists/e-scooterists braking in the same conditions as in this study (i.e., comfort, harsh, and unexpected), and the results are very similar, although the (unassisted) bicycle's harsh braking in their study resulted in a somewhat higher deceleration rate than was found in this study. Because this study had a larger number of subjects, the average value given here is likely to be more accurate than the one presented there. In any case, their results are still well within one standard deviation of this study's, and even this small difference may be explained by the small data sample. Interestingly, both studies found that, in unexpected braking, riders achieve slightly larger deceleration than in planned braking. It is, however, unknown whether the larger deceleration is caused by suggestion (from the expectation of the experimenter's command) or by some other mechanism. The results for bicycle expected braking in this study were similar to those already reported by Lee et al. (2020) from 16 riders, while the results for e-scooter braking were in line with those reported from eight riders by Garman et al. (2020).

Braking performance, in terms of decelerations and braking distances, was similar for the assisted and unassisted bicycle tasks

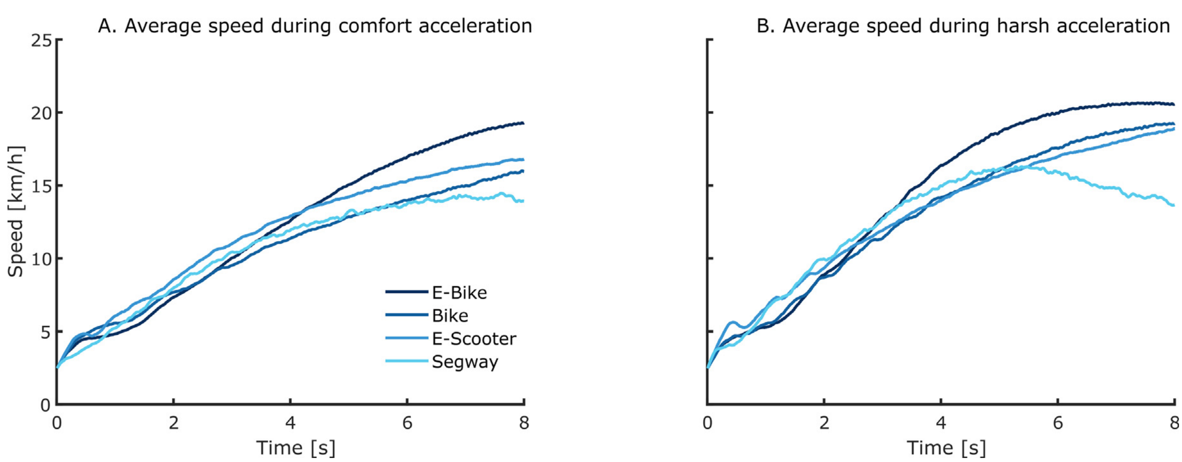

Fig. 3. Average speed for comfort and harsh accelerating maneuvers for all vehicles.

Table 2
Average accelerations (M) with standard deviations (SD) expressed in m/s^2. N indicates the number of trials available for computing averages and standard deviations. We also report the average R2 coefficients to show the goodness of fitness of the linear models.

maneuver	bicycle (M ± SD)	e-bicycle (M ± SD)	e-scooter (M ± SD)	Segway (M ± SD)
Comfort	0.45 ± 0.11 (N = 22; R^2 = 0.96)	0.70 ± 0.12 (N = 26; R^2 = 0.98)	0.56 ± 0.19 (N = 25; R^2 = 0.94)	0.67 ± 0.36 (N = 13; R^2 = 0.93)
Harsh	0.76 ± 0.28 (N = 25; R^2 = 0.96)	0.95 ± 0.14 (N = 26; R^2 = 0.95)	0.70 ± 0.25 (N = 28; R^2 = 0.93)	1.01 ± 0.34 (N = 13; R^2 = 0.95)

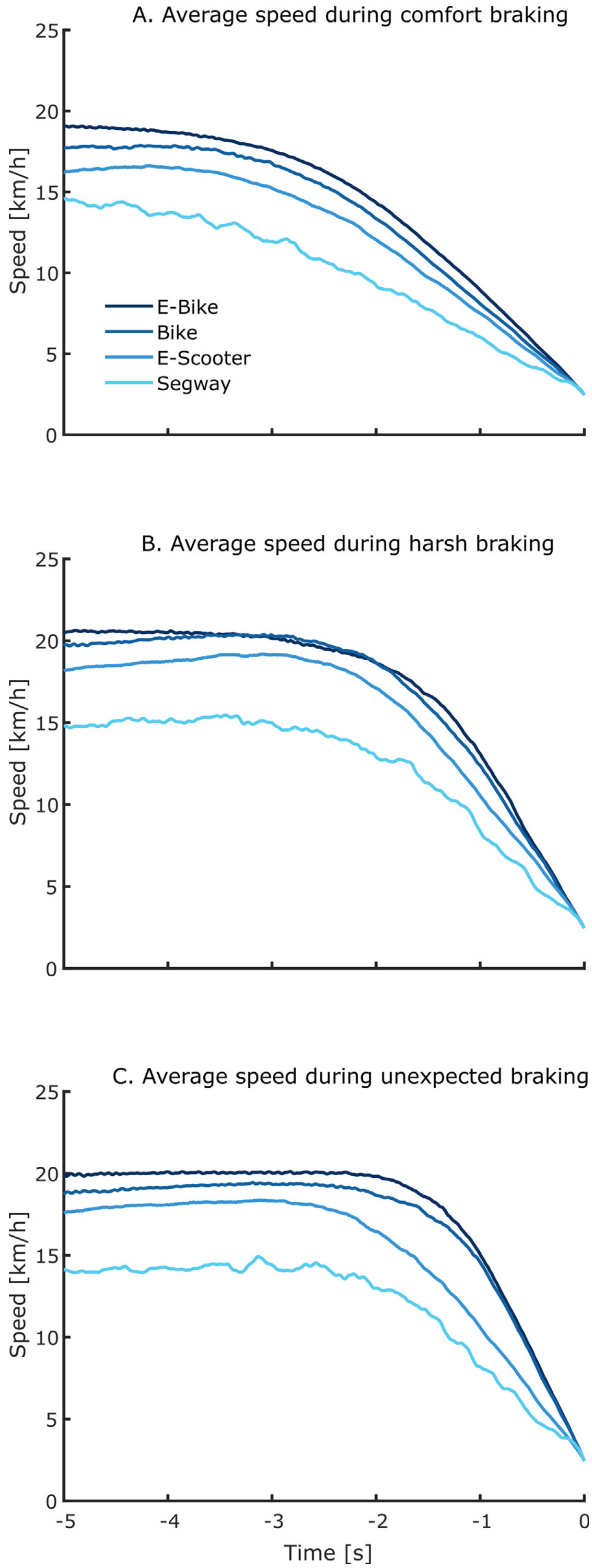

Fig. 4. Average speed for comfort, harsh, and unexpected braking maneuvers for all vehicles.

and poorer for the e-scooter and Segway. Both objective and subjective data suggest that the Segway is less stable and harder to maneuver than the other vehicles. Further, e-scooters seem to be harder to control than bicycles, both because 61% of riders were not able to halt before the stop line and because response times for braking were longer for e-scooters than for all other vehicles. Although steering performance (which is not addressed in this paper) may redeem e-scooters' maneuverability, when it comes to longitudinal control (i.e., crash avoidance by braking), e-scooters and Segways perform much more poorly than bicycles, which raises some concerns about their safety. Riders seem to be aware of these limitations, because the questionnaire data clearly indicate that riders perceive e-scooters and Segways as less stable and safe than bicycles. This result is positive, because riders may be able to use their awareness to compensate for the inferior braking performance by braking in anticipation (earlier), for instance, or using other crash-avoidance strategies.

This study verified that accelerative and braking maneuvers on micromobility vehicles are highly predictable because riders tend to control the vehicles by maintaining constant accelerations. Although the accelerations may change depending on the vehicle and the urgency of the maneuvers, the constancy may make it possible for active safety systems (and automated vehicles) to predict cyclist trajectories. This may be particularly critical at an intersection: a vehicle may estimate the probability that a crossing cyclist will stop at the intersection in time and use this information to warn the driver or apply automated interventions, such as emergency steering and braking (Thalya et al., 2020). Further, by including our models in the threat assessment for warning and intervention systems (SAE J3063), current systems intended to avoid crashes with motorized vehicles (e.g., frontal collision warning, automated emergency braking) may be adapted to also avoid crashes with micromobility vehicles (Boda et al., 2018). As consumer rating programs such as Euro NCAP include new test scenarios with new vulnerable-road-users (Van Ratingen et al., 2016), the results in this paper may be used to derive test scenarios that specify the safety-relevant differences between micromobility solutions. Finally, dynamic geofencing (i.e., algorithms that can remotely control micromobility, for example, by limiting speed) may make use of the data from this study to determine which speeds are safe for different vehicles, depending on the time of day and the location of the rider.

Experience is fundamental for safe riding, especially for new micromobility vehicles (Austin Public Health, 2019). Similarities across vehicles may help a rider to master a new vehicle in a short time. For instance, our participants were much more experienced with traditional bicycles than with electrical bicycles; nevertheless, they perceived the two vehicles similarly and mastered the bicycle equally well with and without assistance. Previous experience from riding a bicycle may not have ported equally well to e-scooters, because the controls and the geometry are very different. Indeed, riding a bicycle is an overlearned skill that required a relatively long time to develop, and we do not know whether riding an e-scooter for the first time would be equally challenging for a rider who does not know how to ride a bicycle. Future studies should investigate the extent to which experience from riding a bicycle may transfer to e-scooter riding and whether, in critical situations, such previous experience may lead to suboptimal avoidance maneuvers (Adams, 1987).

If cycling skills transferred to e-scooter riding, they certainly did not help much with riding a Segway. Only 25 participants completed the experiment with the Segway, and none of them reached the 17–20 km/h speed set by the experimental protocol (although it should have been possible for the Segway to reach this range, according to the specifications from the manufacturer). All participants rated this vehicle lower than all the others for comfort, stability, maneuverability, and safety. Although our correlation analysis shows that these categories are not orthogonal at all, this

Table 3
Average acceleration (M) with standard deviations (SD) expressed in m/s^2. N indicates the number of trials available for computing averages and standard deviations. We also report the average R2 coefficients to show the goodness of fitness of the linear models.

maneuver	bicycle (M ± SD)	e-bicycle (M ± SD)	e-scooter (M ± SD)	Segway (M ± SD)
Comfort	−1.50 ± 0.51 (N = 18; R^2 = 0.97)	−1.65 ± 0.66 (N = 26; R^2 = 0.98)	−1.28 ± 0.42 (N = 20; R^2 = 0.98)	−0.93 ± 0.40 (N = 11; R^2 = 0.96)
Harsh planned	−3.00 ± 1.29 (N = 25; R^2 = 0.98)	−3.10 ± 1.25 (N = 26; R^2 = 0.97)	−2.21 ± 0.59 (N = 28; R^2 = 0.98)	−1.65 ± 0.59 (N = 14; R^2 = 0.93)
Unexpected	−3.60 ± 1.28 (N = 24; R^2 = 0.97)	−3.66 ± 1.07 (N = 24; R^2 = 0.99)	−2.23 ± 0.71 (N = 28; R^2 = 0.99)	−1.60 ± 0.49 (N = 11; R^2 = 0.94)

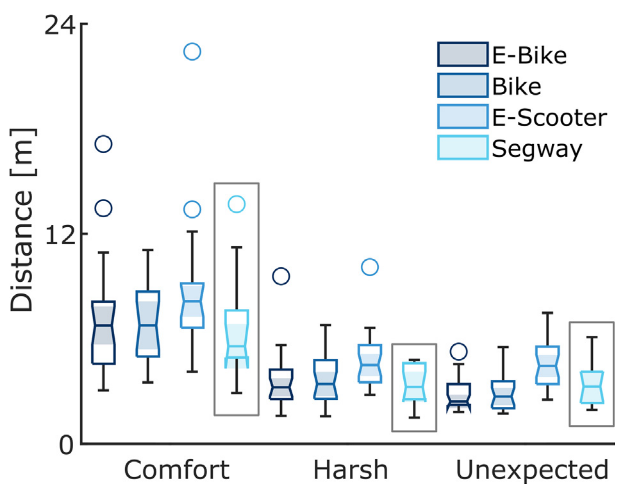

Fig. 5. Boxplots of braking distances for all vehicle types. Circles indicate outliers, whiskers are set by the non-outlier minima and maxima of the distribution, and the center line represents the median, while the horizontal edges of the box are the 25th and 75th percentiles. The notches, highlighted with shading, indicate the confidence intervals. (These boxplots were generated with the boxchart command in Matlab; please refer to its documentation for more detailed information.) The data from the Segway are surrounded by a box to remind the reader that a direct comparison with the other vehicles may be misleading in this specific analysis because the Segway started braking at a lower speed compared to the other vehicles and only few subjects were included in the analysis.

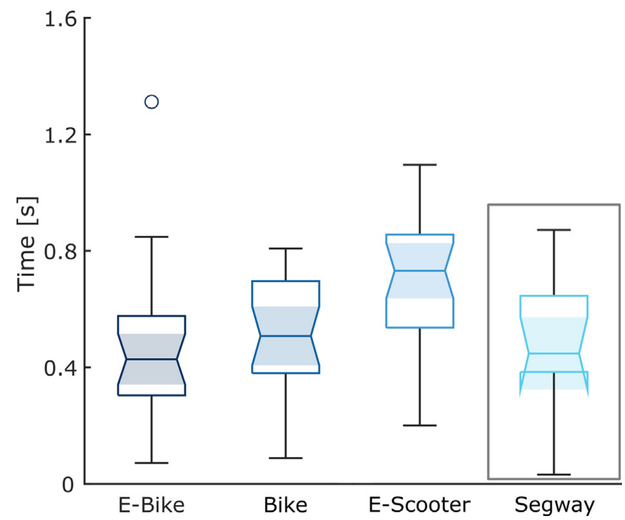

Fig. 6. Response time in unexpected braking across vehicles. Circles indicate outliers, whiskers are set by the non-outlier minima and maxima of the distribution, and the center line represents the median, while the horizontal edges of the box are the 25th and 75th percentiles. The notches, highlighted with shading, indicate the confidence intervals. (These boxplots were generated with the boxchart command in Matlab; please refer to its documentation for more detailed information.) The data from the Segway are surrounded by a box to remind the reader that a direct comparison with the other vehicles may be misleading in this specific analysis because the Segway started braking at a lower speed compared to the other vehicles and only few subjects were included in the analysis.

result is reasonable because the Segway has a different geometry compared to the other vehicles, and its pitch fluctuations may take a while to get used to. None of the participants were acquainted with this vehicle before the experiment, and we do not know whether their inexperience may have affected our results. Nevertheless, this example shows the importance of training on new micromobility vehicles that may look intuitive to ride but are still dangerous, especially on the very first rides, as the report from Austin Public Health (2019) showed for e-scooters. The results presented in this paper suggest that practicing braking to a line marked on the ground and using the possible overshoot distance as feedback may be an easy and useful training for novice Segway users (and possibly for any kind of micromobility vehicle).

E-scooters are mainly ridden by young males (6t-bureau de recherche, 2019; Bjerkan et al., 2020); however, the number of female riders is not negligible. Our study failed to show any statistically significant difference in how female and male riders longitudinally controlled the bicycle, e-bicycle, e-scooter, or Segway. Further, braking distances and response times were similar across gender, and the percentage of females that completed the experiment with the Segway was similar to that of the other vehicles. All in all, we could not verify the common hypothesis that males ride more aggressively or take higher risks than female riders. We did, however, find some effect of age on the subjective data; specifically, the older the subjects were, the lower their ratings were for the e-scooter and the Segway. Although the age span in this study was not large and the effect of age was minor when compared to the effect of vehicle type, our results suggest that younger people are more positive about new micromobility vehicles than older people. This result appears to be in line with previous studies that showed that elderly people are particularly averse to e-scooters (Portland Bureau of Transportation, 2018).

In this study, we lost about 50% of the data from the Segway, in part because the participants were not able to master it; we also lost up to 20% of the data from the other vehicles, mainly because participants had difficulty controlling the speed as they were instructed to. Although this amount of data loss is common in field trials, it may have biased the dataset toward a particularly athletic or daring sub-population of participants, especially for the Segway. It is also worth noting that the experiment was challenging; the one participant who crashed reported a minor injury. While we still believe that the value of this experiment justifies the crash risk that we asked the participants to take, we recommend that the research community not underestimate the risks in these experiments and make sure that the participants are insured.

Although we are not aware of any other study with a larger number of subjects for e-scooter field trials, our sample of 34 participants may not be representative of all ages and geographical locations. In addition, because we collected data in a controlled

Table 4
Average values and ranges of the subjective data for all vehicles (from 1 = Very poor to 7 = Exceptional).

	Bike	E-Bike	E-Scooter	Segway
Accelerating from standing still	4.36 (1–7)	5.64 (2–7)	5.46 (2–7)	5.16 (3–7)
Braking at low speed	5.64 (2–7)	5.70 (2–7)	5.12 (2–7)	4.92 (2–7)
Braking at high speed	5.21 (2–7)	5.33 (2–7)	4.03 (1–7)	3.48 (1–6)
Mounting and dismounting	4.91 (2–7)	5.03 (2–7)	5.67 (2–7)	3.60 (1–7)
Keeping balance at high speed	6.15 (4–7)	6.27 (4–7)	5.70 (3–7)	4.88 (1–7)
Keeping balance at low speed	5.18 (2–7)	5.24 (2–7)	5.30 (2–7)	5.12 (2–7)
Overall comfort	5.33 (2–7)	5.85 (3–7)	5.36 (3–7)	4.60 (2–7)
Overall stability	5.88 (3–7)	5.82 (3–7)	5.33 (3–7)	4.28 (1–7)
Overall maneuverability	5.27 (3–7)	5.46 (3–7)	5.33 (3–7)	4.64 (2–7)
Overall safety	5.85 (3–7)	5.64 (3–7)	4.82 (2–7)	3.80 (1–6)

Table 5
Correlation matrix among the subjective ratings for comfort, stability, maneuverability, and safety. (All coefficients are statistically significant.).

Measure	1	2	3
1.Comfort	–		
2.Stability	0.70	–	
3.Maneuverability	0.66	0.72	–
4.Safety	0.68	0.75	0.61

environment and in repetitive tasks, our results may be biased by the lack of other road users in the surroundings, as well as by the expectancy and habituation that the participants may have developed during the experiment. We presented results for e-bicycles and bicycles; however, we tested the same bicycle with and without electrical assistance. While this choice preserved the vehicle geometry across trials, the e-bicycle was heavier than a conventional bicycle (because of the battery and the motor) and therefore may have been less maneuverable. The e-scooter in this study is representative of the e-scooters that individuals purchase for personal use in Sweden; however, it differs from most of the e-scooters available in sharing systems. Such differences include: suspensions, wheel size, and brakes. Future studies should compare different e-scooter models to determine whether the difference in components affects safety. For instance, the longer response time for e-scooters compared to the other vehicles in this study may be a consequence of the electric braking system of the particular type of e-scooter used.

5. Conclusions and Practical Applications

This study provides further evidence that field data can support the safe integration of micromobility in the transport system. Field data show that different micromobility solutions affect rider behavior in multiple ways and create different constraints for vehicle control. Because e-scooters may brake more poorly than bicycles, steering maneuvers may be a better crash-avoidance strategy for e-scooterists than braking even in situations when a cyclist would be safer braking. Consequently, *infrastructure* that is forgiving of vehicles that run off the road may increase e-scooterists' safety.

The Segway vehicle employed in this study performed poorly in the field trials, and the participants ranked this vehicle as the least comfortable, stable, maneuverable, and safe. Nevertheless, Segways and other two-track vehicles with two wheels are popular, possibly because some of the issues with their safety and stability may disappear with enough training. Therefore, it may be important to *educate* novice users of micromobility vehicles and make sure they ride in real traffic only after a sufficient period of training. The design of the required training to facilitate learning and controlling the new micromobility solutions may be supported by field data such as were presented in this paper.

Because crash avoidance is the best way to avoid injuries when cars share the infrastructure with vulnerable road users, *active safety systems*, and automated emergency braking specifically, should make use of the models from this paper in their threat assessment. This study proved that riders keep accelerations (and decelerations) constant in comfortable and harsh maneuvers; therefore, their trajectories can be reliably predicted by (automated) vehicles. The models presented in this paper provide an indication of the longitudinal control performances (and their variability) that vehicles may expect from micromobility users.

Consumer rating programs, such as the one run by Euro NCAP, may use the models from this study to design the experimental protocols to test crash avoidance systems, such as emergency braking and steering. Further, as tests move toward simulations, the models from this paper may inform the behavior of the *virtual* micromobility users that Euro NCAP may introduce in future test simulations.

As novel micromobility vehicles hit the market and join a transport system where vehicles are increasingly *automated and connected*, it becomes increasingly important to model human behavior so that vehicles may understand and predict it, improving safety for all road users.

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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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2022.10.005.

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