TRB Annual Meeting

Evaluation of AI-based Feedback System for Reducing Sidewalk Riding by Shared e-scooter Users

--Manuscript Draft--

Full Title:	Evaluation of AI-based Feedback System for Reducing Sidewalk Riding by Shared e-scooter Users
Abstract:	The objective of this study was to assess the efficacy of using AI-based auditory feedback and speed limitations on shared e-scooters equipped with computer vision sensors to reduce sidewalk riding. Spin, a US-based micromobility company, provided data from 100 e-scooters in Santa Monica, California: half with activated feedback systems and half with deactivated systems. From November 23, 2022, to February 14, 2023, 488 trips were recorded within Santa Monica. Empirical cumulative distribution function (ECDF) plots and Kolmogorov-Smirnov tests indicate that feedback and speed limitations induced a statistically significant reduction in the fractions of trip time and distance that were spent on sidewalks, and in the length and duration of individual segments of sidewalk riding. The feedback group spent 22% less time and 20% less distance on sidewalks compared to the no-feedback group. To assess whether the feedback decreased the likelihood of choosing the sidewalk as the next surface when the rider is on the street or bike lane, we used a binary logistic regression model. The models' results revealed a statistically significant association between receiving feedback and a reduced inclination to choose the sidewalk as the next surface. These results show that feedback from using onboard cameras and artificial intelligence systems that identify roads, bike lanes, and sidewalks can alter e-scooter users' decisions on where to ride, potentially reducing conflicts between pedestrians and scooter riders and increasing compliance with city ordinances.
Manuscript Classifications:	Data and Data Science; Urban Transportation Data and Information Systems AED20; GPS data; Pedestrians, Bicycles, Human Factors; Human Factors of Infrastructure Design and Operations ACH40; Vehicle Technologies; Pedestrians ACH10; Safety; Policy and Organization; Executive Management Issues; Data for Decisionmaking AJE70; Data interpretation; Information for decision making; Safety; Motorcycles and Mopeds ANF30; Pedestrian and Bicyclist Safety
Manuscript Number:	TRBAM-24-02702
Article Type:	Presentation and Publication
Order of Authors:	Mohammad Mehdi Oshanreh, Master of Science
	Daniel J Malarkey, Master of Science
	Donald W MacKenzie, Ph.D
Additional Information:	
Question	**Response**
The total word count limit is 7500 words including tables. Each table equals 250 words and must be included in your count. Papers exceeding the word limit may be rejected. My word count is:	6904
Is your submission in response to a Call for Papers? (This is not required and will not affect your likelihood of publication.)	No

Evaluation of AI-based Feedback System for Reducing Sidewalk Riding by Shared e-scooter Users

Mohammad Mehdi Oshanreh
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Washington
119 More Hall, Box 352700
Seattle, WA 98195-2700
Email: oshanreh@uw.edu

Daniel Malarkey
Research Scientist
Department of Civil and Environmental Engineering
University of Washington
201 More Hall, Box 352700
Seattle, WA 98195-2700
Email: djmalark@uw.edu

Don MacKenzie
Associate Professor
Department of Civil and Environmental Engineering
University of Washington
201 More Hall, Box 352700
Seattle, WA 98195-2700
Email: dwhm@uw.edu

Word Count: 5904 words +4 table (250 words per table) = 6904 words

Submitted [07/31/2023]

ABSTRACT

The objective of this study was to assess the efficacy of using AI-based auditory feedback and speed limitations on shared e-scooters equipped with computer vision sensors to reduce sidewalk riding. Spin, a US-based micromobility company, provided data from 100 e-scooters in Santa Monica, California: half with activated feedback systems and half with deactivated systems. From November 23, 2022, to February 14, 2023, 488 trips were recorded within Santa Monica. Empirical cumulative distribution function (ECDF) plots and Kolmogorov-Smirnov tests indicate that feedback and speed limitations induced a statistically significant reduction in the fractions of trip time and distance that were spent on sidewalks, and in the length and duration of individual segments of sidewalk riding. The feedback group spent 22% less time and 20% less distance on sidewalks compared to the no-feedback group. To assess whether the feedback decreased the likelihood of choosing the sidewalk as the next surface when the rider is on the street or bike lane, we used a binary logistic regression model. The models' results revealed a statistically significant association between receiving feedback and a reduced inclination to choose the sidewalk as the next surface. These results show that feedback from using onboard cameras and artificial intelligence systems that identify roads, bike lanes, and sidewalks can alter e-scooter users' decisions on where to ride, potentially reducing conflicts between pedestrians and scooter riders and increasing compliance with city ordinances.

Keywords: AI-based feedback; shared e-scooter; micromobility; rider behavior; pedestrian; ECDF; Binary Logistic Regression

INTRODUCTION

Shared electric scooters (e-scooters) have emerged over the past six years as both a promising solution to some existing urban transport challenges and a source of some new challenges. The increasing share of e-scooter use in America since their introduction in 2017 can be attributed to the high adoption of smartphones and easy access to information via mobile applications (*1*). The use of e-scooters, both privately owned and shared, has significantly increased in numerous countries worldwide (*2*). Before the disruptive effects of COVID-19, shared e-scooter trips alone in the U.S. totaled 86 million in 2019. However, due to the pandemic, the number decreased to 33 million in 2020. Nevertheless, shared micromobility ridership in the U.S. made a remarkable recovery in 2021, with a total of 112 million scooter and bike trips, almost reaching pre-pandemic levels. Out of these trips, dockless e-scooters accounted for 62.5 million rides(*3*–*5*). Figure 1 illustrates the total number of trips taken by each micromobility mode from 2018 to 2021.

The introduction of e-scooters has presented significant challenges for cities due to their disruptive and unforeseen impacts (*6*). Ever since their introduction, e-scooters have sparked debates among cities on appropriate regulations and guidelines to address safety, privacy, and equity issues (*7*). While shared e-scooters offer a new alternative for short trips and have the potential to improve the utility of public transit by offering an alternative to walking to and from transit stops, their usage has not always fulfilled that promise and has presented cities with other challenges. Research has shown that at present, e-scooters are not commonly used for commuting purposes or to address first and last-mile connections to transit (*8*–*10*) Instead, they are primarily used for recreational and tourist activities, for example in Washington DC (*10*). Furthermore, the lack of control over how people use e-scooters has led to issues such as sidewalk blockages, cluttering, crashes, and other safety concerns across cities and universities in the United States(*11*, *12*)

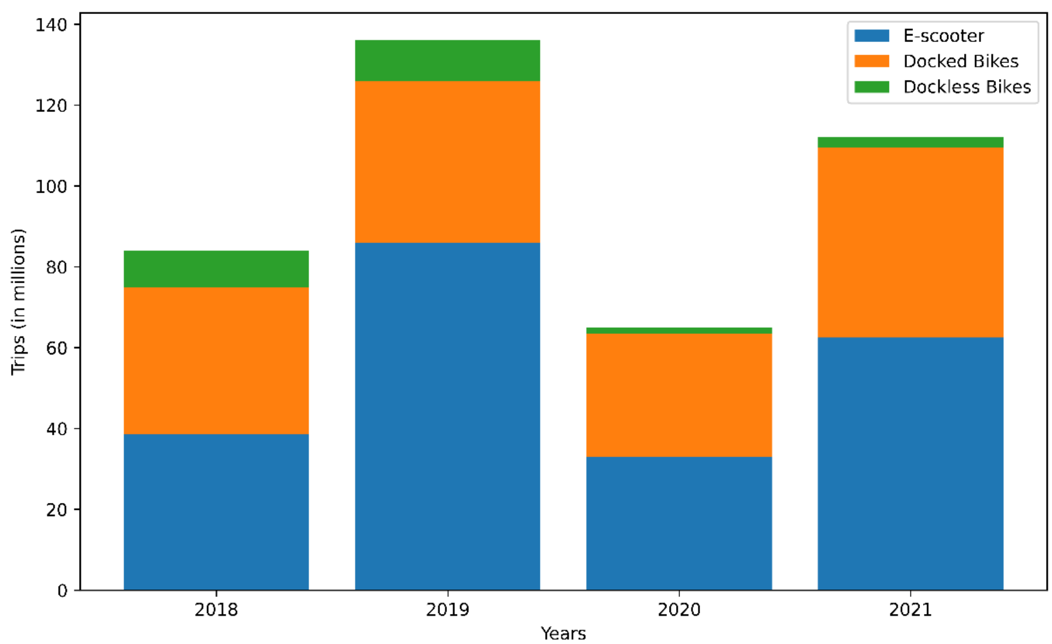

Figure 1 Number of trips made by each shared micromobility mode from 2018 to 2021. Data sourced from NACTO 2018, 2019 and 2022 (*3*–*5*)

LITERATURE REVIEW

One major challenge related to shared e-scooters is safety. The increasing popularity of e-scooters has been accompanied by an increase in e-scooter-related injuries and fatalities, which has drawn the attention of the public and legislators to e-scooter safety (*13–15*). Although several factors impact the operational safety of e-scooters, the lack of dedicated infrastructure for e-scooters is a key contributing factor to safety concerns among e-scooter users (*16*, *17*). Similarly, various studies indicate that e-scooter use is commonly observed in areas with high employment rates and existing bicycle infrastructure, similar to the findings about bikesharing. This suggests that an increase in bicycle infrastructure may lead to a rise in e-scooter usage (*6*, *9*, *18–20*).

The challenges associated with e-scooter use extend to conflicts with pedestrians, particularly when scooters are parked or ridden on the sidewalk, hindering pedestrians' and disabled travelers' movements. Unlike docked devices, dockless e-scooters do not require a dedicated infrastructure for parking, which is an operational advantage for e-scooter companies. According to Peters and MacKenzie (*21*), the setup cost of dockless devices is significantly lower than that of docked ones. In addition, the flexibility of dockless e-scooter services allows for easy redeployment of devices based on demand patterns, which is not feasible with docked services (*21*). As a result, existing infrastructure such as sidewalks are often used for the operation of e-scooters (*22*), contributing to the problem of improper parking obstructing sidewalks, particularly in city downtown areas. This has raised safety concerns, particularly for children, disabled individuals, and those who are visually impaired (*23*, *24*). Improper parking of e-scooters raises concerns among residents and local authorities; however, research by Brown et al. (*23*) suggests that only a small percentage of studied scooters impede pedestrian accessibility. That being said, it should be noted that sidewalk blockage due to improper e-scooter parking is more common in places where sidewalks are narrower since it is more difficult for riders to park e-scooters without impeding access (*22*).

Nevertheless, the shared use of infrastructure and attempts to claim right of way have led to an increase in conflicts between e-scooter riders, pedestrians, and drivers of motor vehicles (*24*). Consequently, in an attempt to avoid conflicts and the hassle of claiming right of way, e-scooter riders often resort to using sidewalks as an alternative to bike lanes. Studies have shown that e-scooter riders prefer to ride on bike lanes, as it provides a safer and more convenient option compared to sidewalks and streets (*17*, *24*). For instance, a study in Alexandria, Virginia found that 53% of e-scooter riders preferred to ride on bike lanes rather than trails, streets, and sidewalks (*3*). Also, a survey from Hoboken, New Jersey, showed that 88% of scooter users felt safer riding on a street if it had a protected bike lane (*3*). A study conducted in Portland, Oregon also showed that scooter riders use bike lanes whenever they are available (*25*).

Based on surveys, sidewalk riding is one of the most concerning issues among pedestrians (*22*, *24*). Sidewalks are typically designed for pedestrian use and are often narrow, which can make it challenging for e-scooter riders to navigate safely alongside pedestrians. Moreover, pedestrians may not be able to hear an approaching e-scooter due to their quiet electric motors, which can increase the risk of collisions. There is significant variation among cities regarding the policies on where e-scooters should be ridden, such as on roads, sidewalks, bike lanes, or multi-use trails (*26*). For instance, in Arlington County, Virginia, sidewalk riding is allowed when there are fewer pedestrians present and riding on streets seems hazardous (*24*); however, sidewalk riding is prohibited in many other states. Even though sidewalk riding is prohibited in Salt Lake City, Badeau et al. (*13*) found that 44% of patients involved in e-scooter-related crashes (22 out of 50) reported their crash had occurred on a sidewalk. Although policies on e-scooter usage vary, there is currently insufficient research evidence to inform decision-making in this regard (*27*).

Countermeasures to improve safety and/or reduce conflicts among road users – not just with e-scooters but in general – can be broadly grouped into infrastructure, vehicle, and behavioral strategies. Infrastructure strategies involve the provision of dedicated infrastructure, signage, signals, and traffic calming approaches to support other modes of transportation rather than motor vehicles. Studies have shown that vegetation and road signages can affect the minimum visibility distance, impacting the safety of road users (*28*, *29*). This means that visual cues such as signs, signals and vegetation can reduce the "looked-but-failed-to-see" phenomenon (*30*). Dedicated infrastructure would also decrease the conflicts between e-scooter riders, drivers, and pedestrians while making micromobility more appealing to people with safety concerns (*11*, *17*, *24*).

Vehicle-based strategies include changes to vehicle design to reduce the probability and/or severity of crashes. Although the ergonomic design of other modes of transportation (e.g., cars and airplanes) has received much attention (*31–33*), little research has addressed this topic in e-scooters. However, Siebert et al. (*34*) found that e-scooter riders choose brake levers solely based on the placement of the lever position, not based on the consideration of which wheel to brake. Consequently, they suggested installing a combined braking system (CBS) on e-scooters would increase the potentially applicable brake power. CBS, which is also called linked braking system (LBS), is a system that links the front and rear brakes of scooters and motorcycles (*35*). Additionally, Yannis et al. (*36*) suggested that pneumatic tires, larger wheel size and frame geometry would increase e-scooter's stability and road grip. They also suggested that brake cables should be protected from accidental damage and vandalism.

Behavioral strategies include real-time driver feedback mechanisms. These are well-established for improving safety in motor vehicles. For example, Lane Departure Warning Systems (LDWS) effectively enhanced drivers' situational awareness (*37*). Cicchino (*27*) found that vehicles equipped with blind spot monitoring technology were involved in crashes 14% less than those without. Speed limiting technology, or so-called Intelligent Speed Adaptation (ISA), is a relatively new technology that limits the maximum speed of the car based on the speed limit of the roadway on which the car is ridden. ISA uses GPS or road sign detection technology to warn drivers when they exceed the speed limit or prevent drivers from exceeding the speed limit (*38*). Behavioral strategies also include establishing and enforcing regulations by governments and/or companies. For example, Voi, an e-scooter company in Europe, offers rewards to riders who upload a selfie photo wearing a helmet at the beginning of their trip. In Richmond, Canada, Lime users are asked to upload a photo of the parked e-scooter to the Lime application at the end of their trip to show that they have parked their e-scooter correctly.

RESEARCH DESIGN

This work evaluates an intervention that sits at the nexus of infrastructure, vehicle, and behavioral strategies: shared e-scooters were equipped with a camera-based AI system to detect the riding surface; users were given feedback and their speed reduced if sidewalk riding was detected; and normal operation was restored when the scooter returned to a street or bike lane.

Spin, a micromobility company based in the United States, deployed 100 such scooters in Santa Monica, California in late 2022. Unlike GPS-based technologies, which are unreliable for detecting sidewalk riding because of their imprecision (*36*), the e-scooters in this study were equipped with an intelligent camera device that can detect the surface on which the user is riding using AI algorithms. Although the primary purpose of these cameras was to assess how the e-scooters were parked at the end of the trips, they also captured the e-scooters' movements on various infrastructure, like streets, bike lanes and sidewalks, thanks to camera computer vision system developed by Drover AI, which can detect the type of surface being traveled upon. Riding on sidewalks is prohibited in Santa Monica. Whenever the rider enters a sidewalk, a combination of feedback alerts and speed limitation are implemented: an in-app push notification, a beeping sound from the e-scooter itself, and a reduction in the maximum speed limit of e-scooter. This feedback and limitations persist unless the rider exits the sidewalk. Since the installation of the cameras on the e-scooters, these feedbacks and restrictions have been applied.

To evaluate the effectiveness of these mechanisms, we worked with Spin to conduct a quasi-experiment. Out of 100 e-scooters equipped with the camera-based AI system, 50 were selected at random to have their user feedback mechanisms disabled starting November 23rd, 2022. However, these scooters were still capable of detecting and recording the surface they were riding on. There was no visual difference between feedback-enabled e-scooters and disabled ones, and riders, if they were already familiar with the feedbacks and limitations, wouldn't have noticed the difference unless they rode on sidewalks. We divided trips into two groups – feedback and no feedback – based on whether the trip was made on an e-scooter with its feedback system enabled or disabled. Even though riders were not assigned randomly into these groups, we assume that the selection of scooters was as good as random for our purpose, since riders would have no way of knowing before a trip if they were selecting an e-scooter with feedback enabled or disabled.

We computed the proportion of time and distance that riders spent riding on sidewalks, streets, and bike lanes. As the data was recorded in the database each time a change in surface type was detected by the AI camera, we inferred that the time and distance between consecutive events corresponded to the prior detected surface type. It's important to note that the camera needs approximately 20 seconds to wake up after an e-scooter is unlocked through the Spin cellphone application; thus, we do not have data about the first 20 seconds of the trip unless the rider starts riding the e-scooter after this period.

DATA

Whenever the Drover AI system detects a change in the surface type on which the e-scooter is being ridden, it transmits data to the database, yielding event-based data. The information sent to the database contains GPS coordinates, trip ID, vehicle ID, timestamp, and detected surface type. The Drover AI system has been in use for more than a year on Spin's scooters, but we only used the data from November 23, 2022, to February 14, 2023, the time during which the subset of e-scooters had their feedback mechanisms disabled. 488 trips both started and ended within the Santa Monica city limits during the study period, 32 of which only had one record in the database. We excluded these 32 trips in our analysis. Table 1 shows the summary statistics of the data.

TABLE 1 Summary Statistics of Trip Times and Origin-Destination (O-D) Distances

	Number of trips	Trip time (Minute)		Origin-Destination network shortest distance (Kilometer)	
		Mean	Std. Dev.	Mean	Std. Dev.
Feedback	289	12.0	13.5	1.1	1.1
No Feedback	167	13.4	14.1	1.1	1.0

We used the OSMnx Python package developed by Geoff Boeing (*39*) to calculate the distance between two successive events in a trip based on their coordinates. Figure 2 displays the distribution of the network shortest path distance between consecutive events within a trip. Since the data is solely based on events and does not provide any information about the rider's path, we assumed that the network shortest path between two consecutive events corresponds to the path taken by the rider. Figure 2 shows that the median non-zero distance between consecutive events is 63 meters. This short distance and Santa Monica's gridded street network make it reasonable to treat this value as the approximate distance covered by the rider between two consecutive events. The spike at 60 meters in Figure 2 corresponds to half the length of a standard city block in Santa Monica. There is another spike at 120 meters which corresponds to a standard city block length in Santa Monica.

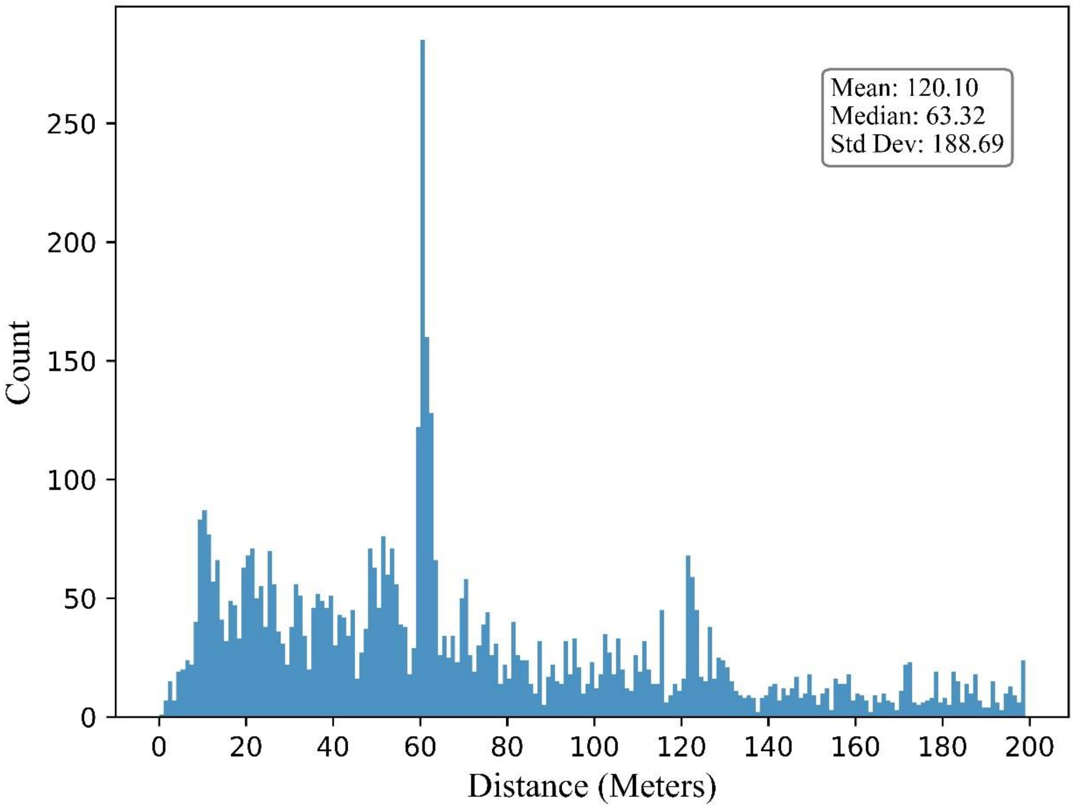

FIGURE 2 Histogram of Non-zero Network Shortest Path Distance Between Consecutive Events within a Trip

METHOD

We plotted empirical cumulative distribution functions (ECDFs) of various trip-level and event-level variables for both the feedback and no-feedback groups and used the Kolmogorov-Smirnov (K-S) test for differences between the distributions of the two groups. These methods are very flexible, making them ideal for analyzing data that may not conform to common parametric assumptions, such as normality or homoscedasticity, and providing a robust alternative for assessing similarities and differences between groups. The K-S test is a statistical method that can assess differences between two underlying one-dimensional probability distributions. The null hypothesis of the two-sample K-S test is that both samples are drawn from the same continuous distribution.

Using ECDF and K-S tests, we have evaluated the differences between feedback and no-feedback e-scooters on each surface type: sidewalk, bike lane, and street. We have compared the trip-total time and total distance on each surface for both scooter types and tested for differences in the distributions of these values between the feedback and no-feedback groups.

Furthermore, we have investigated the fractions of trip time and distance spent on each surface, as well as the length and duration of individual event times on each surface.

Finally, we employed a binary logistic regression model to examine the relationship between being on a feedback-enabled scooter and the likelihood of selecting the sidewalk as the next surface for riding.

RESULTS

To evaluate the differences between the feedback and no-feedback groups, we used three different measures which are discussed in turn in the following subsections:

- segment time and distance on each surface, at the individual event level

- fraction of time and distance on each surface type, at the trip level
- total time and distance on each surface type, at the trip level

Finally, we present state transition matrixes for each group, illustrating the states (surface types), as well as the results of the binary logistic models.

Individual-event Level Segment of Time and Distance on Each Surface

In this subsection, we examine the individual events within each trip. We computed the time and distance between consecutive events within a trip. Following that, we created ECDF plots to represent the time and distance distributions for both groups. We used the K-S test to assess whether the two ECDFs were drawn from the same underlying distribution.

Figures 3 and 4 show the ECDFs for the duration and distance on each surface, measured at the level of individual segments between consecutive events. They show a modest but statistically highly significant reduction in both the length and duration of individual segments of sidewalk riding.

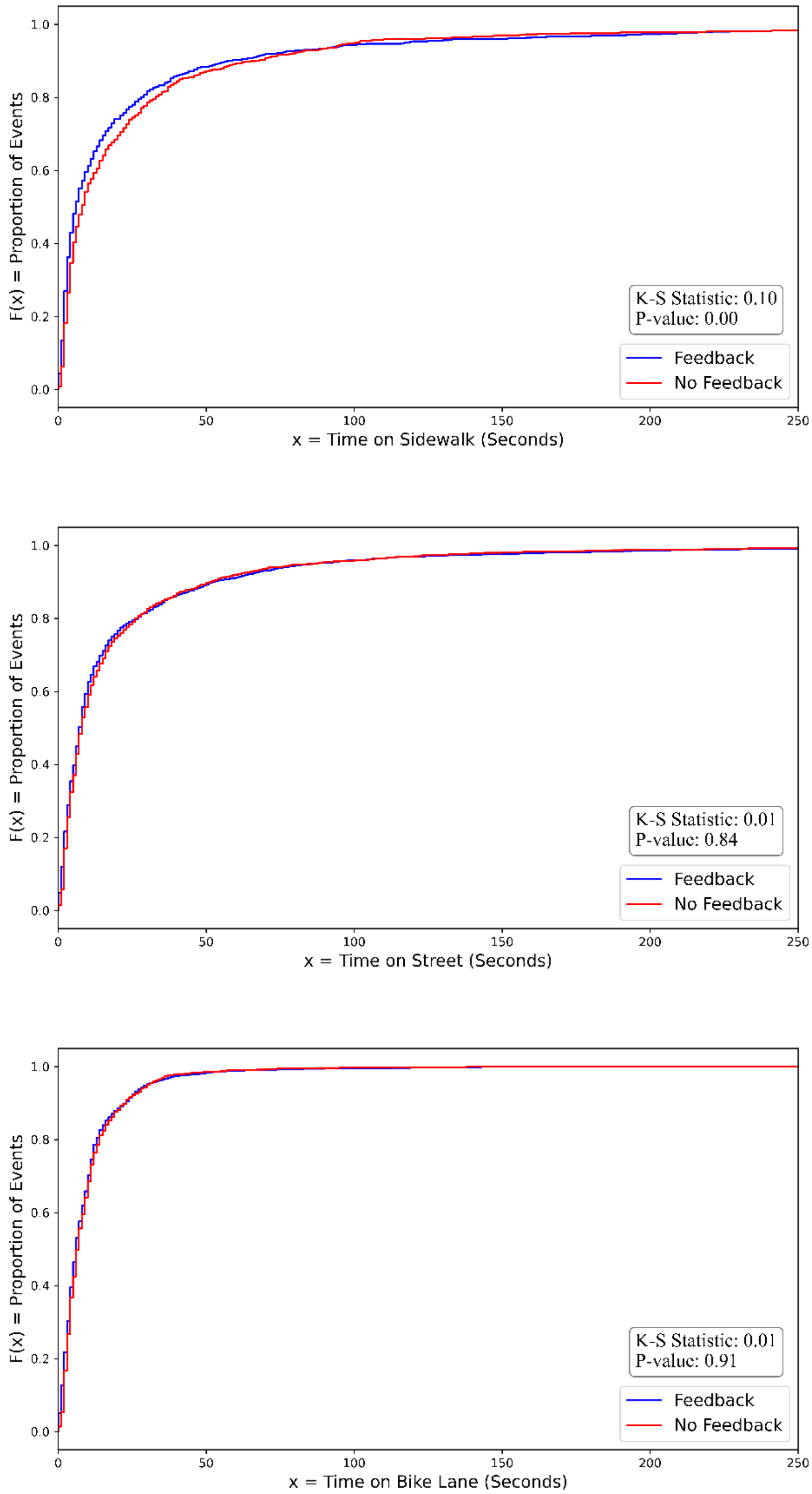

FIGURE 3 ECDFs of Time Ridden on Each Surface Type for Feedback and No-feedback Groups, at Individual Event Level.

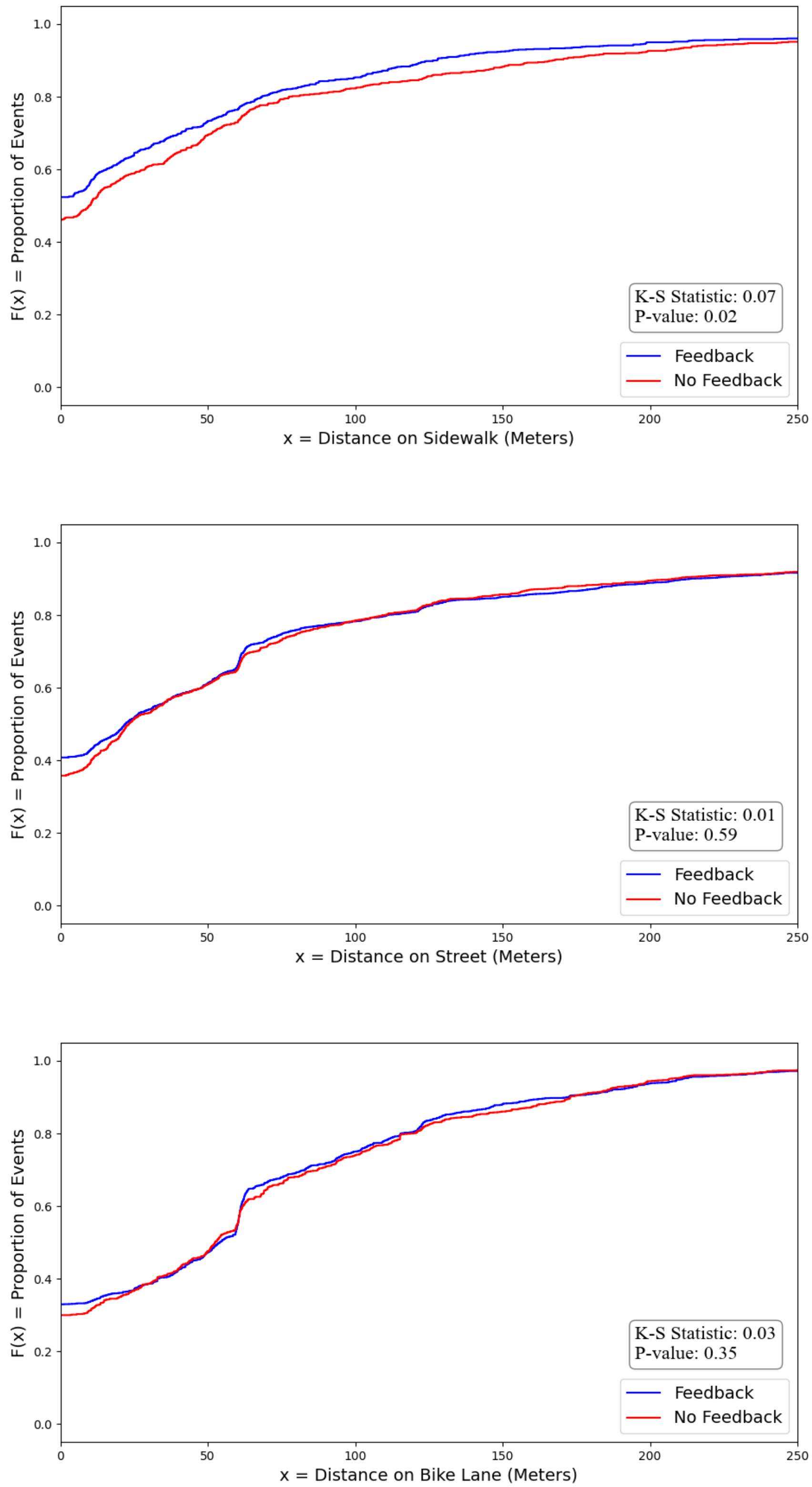

FIGURE 4 ECDFs of Distance Ridden on Each Surface Type for Feedback and No-feedback Groups, at Individual Event Level.

Trip-level Total Time and Distance on Each Surface

In this subsection, we computed the total time and distance that the e-scooter traveled on each surface category for each trip. Figures 5 and 6 show the ECDFs for the total time and total distance on each surface, measured at the level of complete trips. Directionally, the ECDFs indicate a reduction in the time traveled on sidewalks, but this shift is significant only at the 0.1 level.

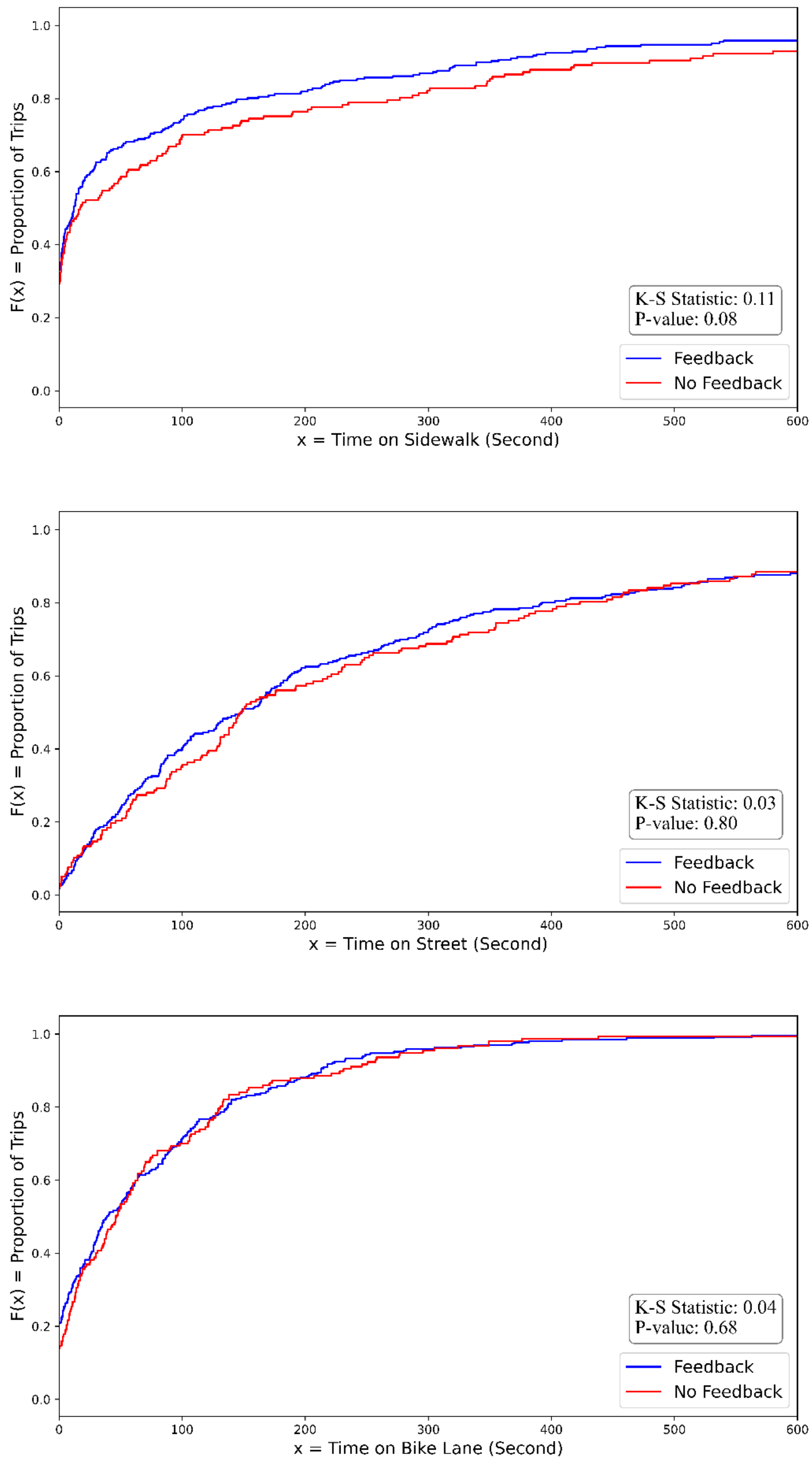

FIGURE 5 ECDFs of Total Time Ridden on Each Surface Type for Feedback and No-feedback Groups, at Trip Level.

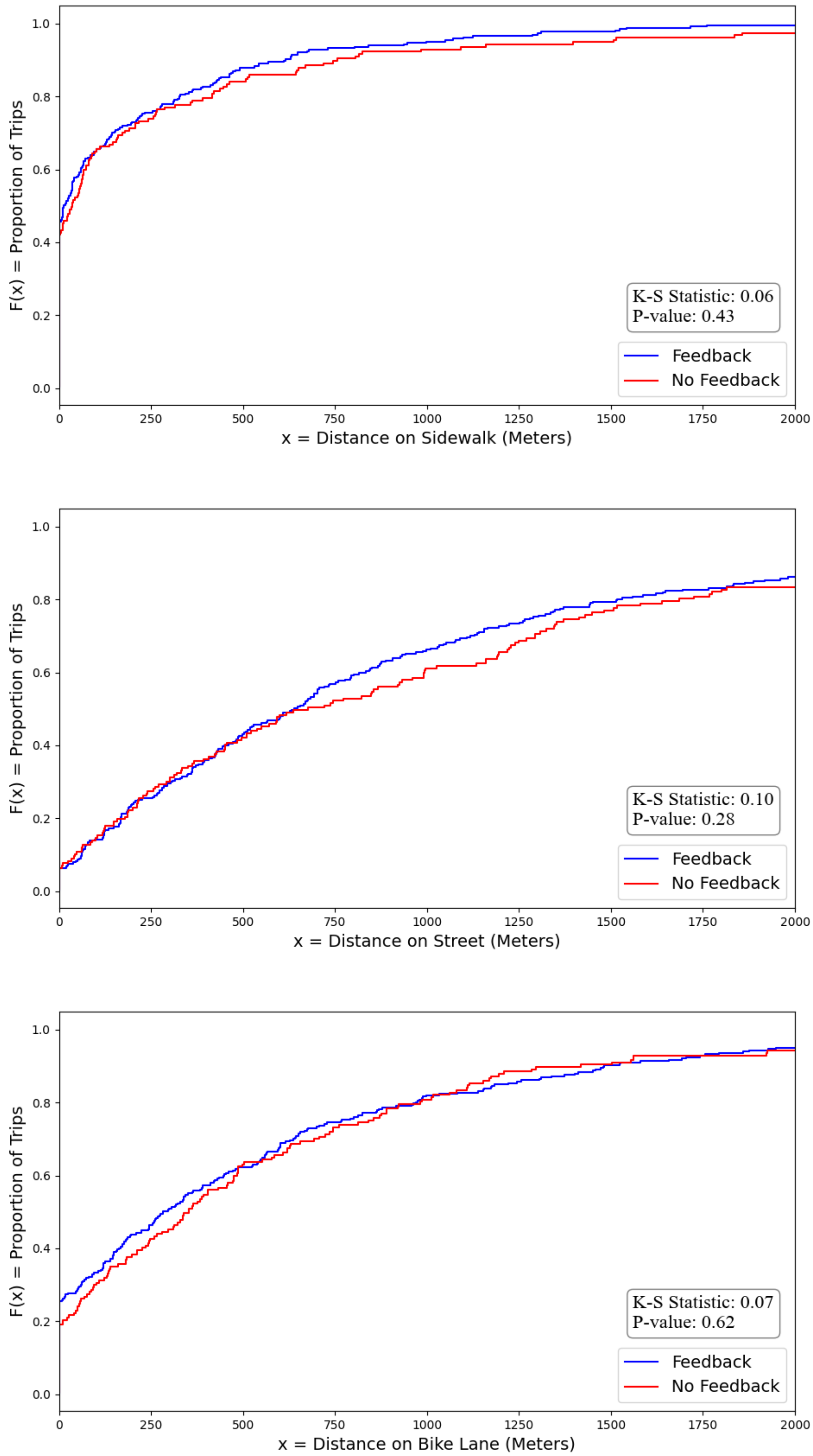

FIGURE 6 ECDFs of Total Distance Ridden on Each Surface Type for Feedback and No-feedback Groups, at Trip Level.

Trip-level Fraction of Time and Distance on Each Surface

To adjust for any potential differences in overall trip length between the feedback and no-feedback groups, we next examined the fraction of total trip time and fraction of total trip distance that were spent on each surface type. The analysis followed the same pattern as in the preceding subsection. The corresponding ECDF plots for time and distance are shown in figures 7 and 8, respectively. Directionally, feedback group spend less fraction of trip time and distance on sidewalk and the K-S result shows a significant reduction in fraction of time ridden on sidewalk.

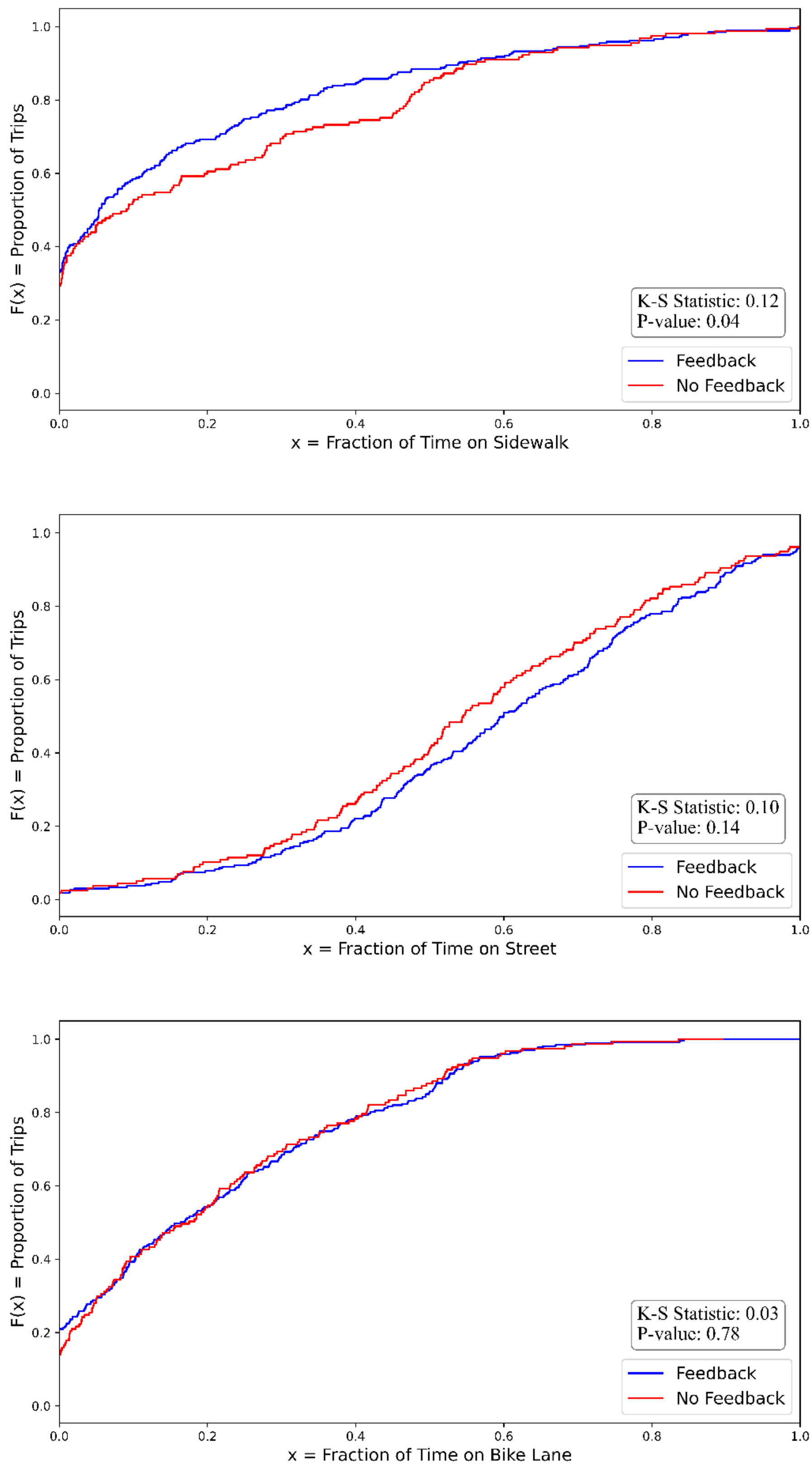

FIGURE 7 ECDFs of Fraction of Time Ridden on Each Surface Type for Feedback and No-feedback Groups, at Trip Level.

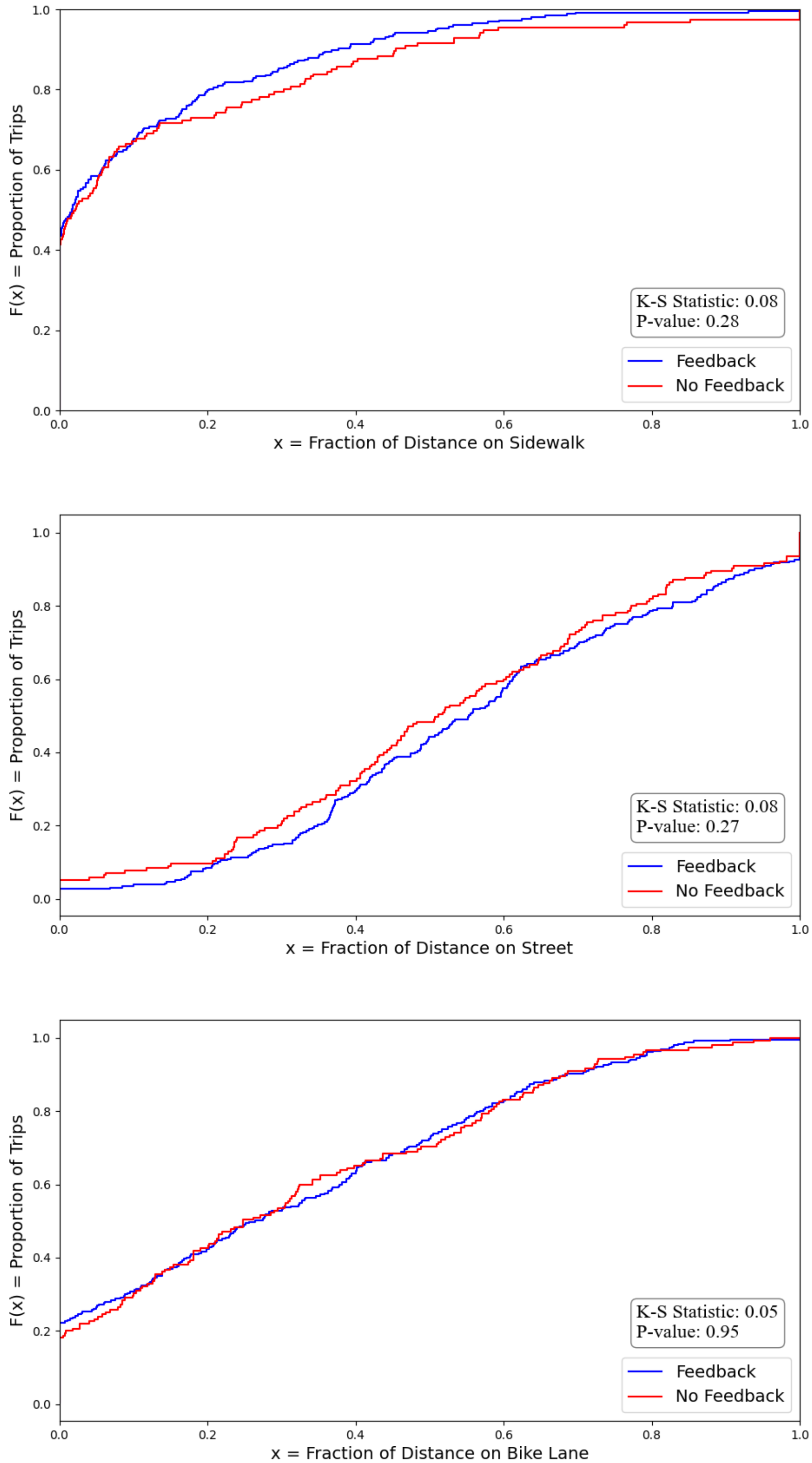

FIGURE 8 ECDFs of Fraction of Distance Ridden on Each Surface Type for Feedback and No-feedback Groups, at Trip Level.

Markov State Transition Diagram and Binary Logistic Regression Results

The camera-based AI system transmits data to the server whenever it detects a change in the state of the e-scooter, in this case, the surface type. This results in event-based data, which allows us to determine the frequency of transitioning from one state to another. We obtained state transition matrices for the feedback and no-feedback groups by calculating and normalizing these frequencies. Table 2 reports the state transition matrices for the feedback and no-feedback groups. In comparison to the no-feedback group, the feedback group was less likely to move from street to sidewalk or from bike lane to sidewalk.

TABLE 2 State Transition Matrix for Feedback and No-feedback Groups

To / From	Street		Sidewalk		Bike lane	
	Feedback	No feedback	Feedback	No feedback	Feedback	No feedback
Street	0	0	0.32	0.38	0.68	0.62
Sidewalk	0.88	0.89	0	0	0.12	0.11
Bike Lane	0.96	0.94	0.04	0.06	0	0

To test the significance of the feedback on reducing the likelihood of choosing sidewalk as the next surface to ride on, we fitted two binary logit models on events that started from street and bike lane respectively. Equation 1 is the regression model.

$$P(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X)}} \quad (1)$$

In the first model, P(Y=1) represents the probability of choosing the sidewalk as the destination while currently riding on the street. In the second model, P(Y=1) indicates the probability of choosing the sidewalk as the destination while currently riding on the bike lane. The independent variable X is a dummy variable, where X equals 1 if the trip was made by a scooter in the feedback group, and 0 otherwise. β_0 is the intercept and β_1 is the coefficient of the dummy variable. Table 3 shows the logistic regression results for transition states starting from street.

TABLE 3 Logistic Regression Result for Transition States with Street as the Prior Event

Coefficient	**Estimate**	**Std. Err**	**Z**	***p***	**95% CI**	
					2.5 %	97.5%
$\boldsymbol{\beta_0}$	-0.589	0.048	-12.230	<0.001	-0.684	-0.495
$\boldsymbol{\beta_1}$	-0.160	0.062	-2.592	0.01	-0.282	-0.039
No. Observations: 4910 Df Residuals: 4908 Df Model: 1 Pseudo R-squ: 0.001070 Log-Likelihood: -3125.6 LL-Null: -3129.0 LLR p-value: 0.009664						

The statistically significant, negative estimate of the coefficient β_1 indicates that receiving feedback is associated with a decreased likelihood of choosing the sidewalk as the next surface to ride when riders are currently riding on street.

Table 4 shows the logistic regression results for transitions starting from bike lane. Even though the coefficient of dummy variable is less than zero, it is not statistically significant, thus, we fail to reject the null hypothesis that the feedback system has no effect on movements from the bike lane to other surfaces.

TABLE 4 Logistic Regression Result for Transition States with Bike Lane as the Prior Event

Coefficient	Estimate	Std. Err	Z	*p*	95% CI	
					2.5 %	97.5%
β_0	-2.671	0.113	-23.681	<0.001	-2.893	-2.451
β_1	-0.225	0.148	-1.518	0.129	-0.516	0.066

No. Observations: 3478
Df Residuals: 3476
Df Model: 1
Pseudo R-squ: 0.001498
Log-Likelihood: -758.57
LL-Null: -759.71
LLR p-value: 0.1314

DISCUSSION AND CONCLUSION

Directionally, the results of this work indicate that the total time, and the fraction of time and distance, traversed on sidewalks was lower for the feedback group than for the no-feedback group. For total time, the difference was significant at the 0.1 level. For the fraction of time, the difference was significant at the 0.05 level, while the difference in fraction of distance was not significant. Though not statistically significant, the rise in time spent riding on streets within the feedback group has a logical and meaningful direction. As the feedback group dedicates less time to riding on sidewalks, they appear to spend a larger amount of their time on streets.

In terms of the fraction of total trip time and distance spent on each surface, the feedback group spent 22% less time and 20% less distance on sidewalks. The results suggested that the feedback group spent 5% more time on streets compared to the no-feedback group. Although there was a 6% increase in the distance traveled on streets for the feedback group relative to the no-feedback group, the K-S test result was not statistically significant. Since most of the trip segments occurred on sidewalks and streets, no differences were apparent in the time or distance spent in bike lanes. This is also consistent with riders already using bike lanes when they are available.

By analyzing the ECDF plots, we can gain a deeper understanding of the riding behavior within each group. For instance, in Figure 7, it is apparent that nearly half of riders spent less than 10% of their time riding on sidewalks, even when feedback was disabled. At the same time, about 1 in 10 riders spent more than 60% of their time on the sidewalk, and this did not change when rider feedback was given. This suggests that individuals who predominantly ride on sidewalks will continue to do so, regardless of whether they receive feedback or not. In contrast, those who spend most of their time on surfaces other than sidewalks are unable to decrease their relative time spent riding on sidewalks. However, in between these groups, about 40% of riders showed a reduction of about 10% in time spent on sidewalks.

One possible explanation for this observation could be the common practice of parking e-scooters on sidewalks, with trips usually starting and ending on these surfaces. Consequently, riders may need to use sidewalks at the beginning or end of their trips to either access an appropriate route leading away from the sidewalk or find a suitable parking location on the sidewalk. This inherent aspect of e-scooter usage may make it challenging for riders to fully avoid sidewalks, even when they primarily use other surfaces for most of their trip. The camera device used in our study requires a 20-second reboot time, which hinders our ability to make conclusions about whether scooter riders intentionally use sidewalks at the beginning of their journey, or if they later transition to bike lanes or streets. As a result, additional research is required to shed light on how scooter riders initiate their trips, and whether they persist in using sidewalks even when safer alternatives, such as bike lanes or streets, are available.

The state transition matrices and binary logistic modeling results suggest that when riders are currently riding on the street and receive feedback, they are less likely to choose the sidewalk as the next surface to ride on. However, when riding on bike lanes and receiving feedback, there is no significant decrease in the likelihood of choosing the sidewalk as the next surface. This lack of significant difference could be due to the fact that most trips occur on streets and sidewalks, making the likelihood of choosing the next surface when riding on a bike lane similar to that when riding on the street.

One final interesting result was the relatively low use of bike lanes, since past research suggests that e-scooter riders generally prefer these designated lanes. Further investigation could explore if e-scooter users consistently choose bike lanes when available, and the low use of bike lanes in this study was due to low bike lane availability or to riders declining to use them even when available.

One limitation of this work is that we lacked access to complete e-scooter trajectory data. With that data, spatial analysis could be conducted to pinpoint areas with higher sidewalk riding rates. Furthermore, more research is needed to determine the most effective combination of feedback and restrictions to discourage e-scooter riders from using sidewalks. In some cases, sidewalks may be safer when bike lanes are unavailable and traffic is heavy. Future studies should explore the safety implications of sidewalk riding in such situations. Ideally, this technology could help riders make informed decisions about using available infrastructure responsibly. In instances where bike lanes are absent, and streets are unsafe for riding, sidewalks could be utilized, provided that speeds are reduced to a reasonable level to ensure the safety of both pedestrians and riders.

During our study, we encountered several practical challenges that affected our ability to collect data. One of the most notable challenges was an organized theft ring that targeted the camera-equipped e-scooters that were the subject of the study. As a result of this issue, Spin decided to remove all camera-equipped scooters from service. This reduced the number of recorded trips, which impacted the amount of data that we were able to collect and may have affected the statistical power of our analysis. Given the theft issues that we encountered during our study, we believe that further research is needed to explore the safety implications of equipping e-scooters with cameras. Such studies could help inform the development of effective safety and security measures and protocols that prevent thefts and ensure the safety of e-scooter riders.

ACKNOWLEDGMENTS

The work was supported by the U.S. Department of Transportation (DOT) via Connected Cities for Smart Mobility towards Accessible and Resilient Transportation (C2SMART) Center awarded by the U.S. Department of Transportation under contract 69A3551747119. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Mohammad Mehdi Oshanreh, Daniel Malarkey, Don MacKenzie; data collection: Mohammad Mehdi Oshanreh, Daniel Malarkey, Don MacKenzie; analysis and interpretation of results: Mohammad Mehdi Oshanreh, Don MacKenzie; draft manuscript preparation: Mohammad Mehdi Oshanreh, Daniel Malarkey, Don MacKenzie. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Button, K., H. Frye, and D. Reaves. Economic Regulation and E-Scooter Networks in the USA. *Research in Transportation Economics*, Vol. 84, 2020, p. 100973. https://doi.org/10.1016/j.retrec.2020.100973.
2. Lee, M., J. Y. Chow, G. Yoon, and B. Y. He. Forecasting E-Scooter Competition with Direct and Access Trips by Mode and Distance in New York City. *arXiv preprint arXiv:1908.08127*, 2019.
3. NACTO in 2020: Cities Taking the Lead. *National Association of City Transportation Officials*. https://nacto.org/2021/02/16/nacto-in-2020-cities-taking-the-lead. Accessed Dec. 27, 2022.
4. Shared Micromobility in the U.S.: 2019 | *National Association of City Transportation Officials*. https://nacto.org/shared-micromobility-2019/. Accessed Dec. 24, 2022.
5. Shared Micromobility in the U.S.: 2018 | *National Association of City Transportation Officials*. https://nacto.org/shared-micromobility-2018/. Accessed Apr. 22, 2022.
6. Caspi, O., M. J. Smart, and R. B. Noland. Spatial Associations of Dockless Shared E-Scooter Usage. *Transportation Research Part D: Transport and Environment*, Vol. 86, 2020, p. 102396.
7. Tuncer, S., E. Laurier, B. Brown, and C. Licoppe. Notes on the Practices and Appearances of E-Scooter Users in Public Space. *Journal of Transport Geography*, Vol. 85, 2020, p. 102702. https://doi.org/10.1016/j.jtrangeo.2020.102702.
8. Zakhem, M., and J. Smith-Colin. Micromobility Implementation Challenges and Opportunities: Analysis of e-Scooter Parking and High-Use Corridors. *Transportation Research Part D: Transport and Environment*, Vol. 101, 2021, p. 103082. https://doi.org/10.1016/j.trd.2021.103082.
9. Liu, M., S. Seeder, and H. Li. Analysis of E-Scooter Trips and Their Temporal Usage Patterns. *Institute of Transportation Engineers. ITE Journal*, Vol. 89, No. 6, 2019, pp. 44–49.
10. McKenzie, G. Spatiotemporal Comparative Analysis of Scooter-Share and Bike-Share Usage Patterns in Washington, DC. *Journal of transport geography*, Vol. 78, 2019, pp. 19–28.
11. Gössling, S. Integrating E-Scooters in Urban Transportation: Problems, Policies, and the Prospect of System Change. *Transportation Research Part D: Transport and Environment*, Vol. 79, 2020, p. 102230.
12. Younes, H., Z. Zou, J. Wu, and G. Baiocchi. Comparing the Temporal Determinants of Dockless Scooter-Share and Station-Based Bike-Share in Washington, DC. *Transportation Research Part A: Policy and Practice*, Vol. 134, 2020, pp. 308–320.
13. Badeau, A., C. Carman, M. Newman, J. Steenblik, M. Carlson, and T. Madsen. Emergency Department Visits for Electric Scooter-Related Injuries after Introduction of an Urban Rental Program. *The American Journal of Emergency Medicine*, Vol. 37, No. 8, 2019, pp. 1531–1533. https://doi.org/10.1016/j.ajem.2019.05.003.
14. Bai, S., and J. Jiao. Dockless E-Scooter Usage Patterns and Urban Built Environments: A Comparison Study of Austin, TX, and Minneapolis, MN. *Travel Behaviour and Society*, Vol. 20, 2020, pp. 264–272. https://doi.org/10.1016/j.tbs.2020.04.005.
15. Trivedi, T. K., C. Liu, A. L. M. Antonio, N. Wheaton, V. Kreger, A. Yap, D. Schriger, and J. G. Elmore. Injuries Associated With Standing Electric Scooter Use. *JAMA Network Open*, Vol. 2, No. 1, 2019, p. e187381. https://doi.org/10.1001/jamanetworkopen.2018.7381.
16. Kondor, D., X. Zhang, M. Meghjani, P. Santi, J. Zhao, and C. Ratti. Estimating the Potential for Shared Autonomous Scooters. *IEEE Transactions on Intelligent Transportation Systems*, Vol. PP, 2021. https://doi.org/10.1109/TITS.2020.3047141.
17. Ma, Q., H. Yang, A. Mayhue, Y. Sun, Z. Huang, and Y. Ma. E-Scooter Safety: The Riding Risk Analysis Based on Mobile Sensing Data. *Accident Analysis & Prevention*, Vol. 151, 2021, p. 105954. https://doi.org/10.1016/j.aap.2020.105954.
18. El-Assi, W., M. Salah Mahmoud, and K. Nurul Habib. Effects of Built Environment and Weather on Bike Sharing Demand: A Station Level Analysis of Commercial Bike Sharing in Toronto. *Transportation*, Vol. 44, No. 3, 2017, pp. 589–613. https://doi.org/10.1007/s11116-015-9669-z.
19. Heinen, E., B. van Wee, and K. Maat. Commuting by Bicycle: An Overview of the Literature. *Transport Reviews*, Vol. 30, No. 1, 2010, pp. 59–96. https://doi.org/10.1080/01441640903187001.

20. Wang, K., G. Akar, and Y.-J. Chen. Bike Sharing Differences among Millennials, Gen Xers, and Baby Boomers: Lessons Learnt from New York City's Bike Share. *Transportation Research Part A: Policy and Practice*, Vol. 116, 2018, pp. 1–14. https://doi.org/10.1016/j.tra.2018.06.001.
21. Peters, L., and D. MacKenzie. The Death and Rebirth of Bikesharing in Seattle: Implications for Policy and System Design. *Transportation Research Part A: Policy and Practice*, Vol. 130, 2019, pp. 208–226. https://doi.org/10.1016/j.tra.2019.09.012.
22. James, O., J. I. Swiderski, J. Hicks, D. Teoman, and R. Buehler. Pedestrians and E-Scooters: An Initial Look at E-Scooter Parking and Perceptions by Riders and Non-Riders. *Sustainability*, Vol. 11, No. 20, 2019, p. 5591. https://doi.org/10.3390/su11205591.
23. Brown, A., N. J. Klein, C. Thigpen, and N. Williams. Impeding Access: The Frequency and Characteristics of Improper Scooter, Bike, and Car Parking. *Transportation Research Interdisciplinary Perspectives*, Vol. 4, 2020, p. 100099. https://doi.org/10.1016/j.trip.2020.100099.
24. Sandt, L., Transportation Research Board, and National Academies of Sciences, Engineering, and Medicine. *E-Scooter Safety: Issues and Solutions*. Transportation Research Board, Washington, D.C., 2022.
25. 2019 E-Scooter Report | Portland.Gov. https://www.portland.gov/transportation/escooterpdx/2019-e-scooter-report. Accessed Dec. 27, 2022.
26. Chang, A., L. Miranda-Moreno, L. Sun, and R. Clewlow. *Trend or Fad? Deciphering the Enablers of Micromobility in the U.S.* 2019.
27. Cicchino, J. B., P. E. Kulie, and M. L. McCarthy. Severity of E-Scooter Rider Injuries Associated with Trip Characteristics. *Journal of Safety Research*, Vol. 76, 2021, pp. 256–261. https://doi.org/10.1016/j.jsr.2020.12.016.
28. Calvi, A. Does Roadside Vegetation Affect Driving Performance?: Driving Simulator Study on the Effects of Trees on Drivers' Speed and Lateral Position. *Transportation Research Record*, Vol. 2518, No. 1, 2015, pp. 1–8. https://doi.org/10.3141/2518-01.
29. Ma, C., D. Yang, J. Zhou, Z. Feng, and Q. Yuan. Risk Riding Behaviors of Urban E-Bikes: A Literature Review. *International Journal of Environmental Research and Public Health*, Vol. 16, No. 13, 2019, p. 2308. https://doi.org/10.3390/ijerph16132308.
30. della Mura, M., S. Failla, N. Gori, A. Micucci, and F. Paganelli. E-Scooter Presence in Urban Areas: Are Consistent Rules, Paying Attention and Smooth Infrastructure Enough for Safety? *Sustainability*, Vol. 14, No. 21, 2022, p. 14303. https://doi.org/10.3390/su142114303.
31. Bhise, V. *Ergonomics in the Automotive Design Process*. 2016.
32. Kelly, D., and M. Efthymiou. An Analysis of Human Factors in Fifty Controlled Flight into Terrain Aviation Accidents from 2007 to 2017. *Journal of safety research*, Vol. 69, 2019, pp. 155–165.
33. Regan, M. A., and C. Hallett. Chapter 20 - Driver Distraction: Definition, Mechanisms, Effects, and Mitigation. In *Handbook of Traffic Psychology* (B. E. Porter, ed.), Academic Press, San Diego, pp. 275–286.
34. Siebert, F. W., M. Ringhand, F. Englert, M. Hoffknecht, T. Edwards, and M. Rötting. Braking Bad – Ergonomic Design and Implications for the Safe Use of Shared E-Scooters. *Safety Science*, Vol. 140, 2021, p. 105294. https://doi.org/10.1016/j.ssci.2021.105294.
35. Teoh, E. Effectiveness of Antilock Braking Systems in Reducing Motorcycle Fatal Crash Rates. *Traffic injury prevention*, Vol. 12, 2011, pp. 169–73. https://doi.org/10.1080/15389588.2010.541308.
36. Yannis, G., O. Léon, P. Crist, and A. Santacreu. *Safe Micromobility*. 2020.
37. Spence, C., and C. Ho. Multisensory Warning Signals for Event Perception and Safe Driving. *Theoretical Issues in Ergonomics Science*, Vol. 9, No. 6, 2008, pp. 523–554.
38. van der Pas, J. W. G. M., V. A. W. J. Marchau, W. E. Walker, G. P. van Wee, and S. H. Vlassenroot. ISA Implementation and Uncertainty: A Literature Review and Expert Elicitation Study. *Accident Analysis & Prevention*, Vol. 48, 2012, pp. 83–96. https://doi.org/10.1016/j.aap.2010.11.021.

39. Boeing, G. OSMnx: New Methods for Acquiring, Constructing, Analyzing, and Visualizing Complex Street Networks. *Computers, Environment and Urban Systems*, Vol. 65, 2017, pp. 126–139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004.