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Evaluating the Effectiveness of Computer Vision Systems Mounted on Shared Electric Kick Scooters to Reduce Sidewalk Riding

April 2023

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Evaluating the Effectiveness of Computer Vision Systems Mounted on Shared Electric Kick Scooters to Reduce Sidewalk Riding		5. Report Date April 2023
		6. Performing Organization Code:
7. Author(s) Mohammad Mehdi Oshanreh, Donald MacKenzie, Daniel Malarkey		8. Performing Organization Report No.
9. Performing Organization Name and Address Connected Cities for Smart Mobility towards Accessible and Resilient Transportation Center (C2SMART), 6 Metrotech Center, 4th Floor, NYU Tandon School of Engineering, Brooklyn, NY, 11201, United States		10. Work Unit No.
		11. Contract or Grant No. 69A3551747119
12. Sponsoring Agency Name and Address Office of Research, Development, and Technology Federal Highway Administration 6300 Georgetown Pike McLean, VA 22101-2296		13. Type of Report and Period Final report, 6/1/2022 - 4/30/2023
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

The objective of this study was to assess the impact of feedback and speed limitations on the riding behavior of e-scooter riders on sidewalks. To do this, we used data provided by Spin, a US-based micromobility company, on Santa Monica e-scooters that were equipped with an AI camera to monitor surface type. We conducted an experiment in which 50 e-scooters had their feedback mechanisms turned off, while the rest 50 had them on. The study was conducted from November 23, 2022 to February 14, 2023, during which time 488 trips were made within the city of Santa Monica, California. We analyzed the data by calculating the time and distance between consecutive events within a trip, and assuming the distance between two GPS coordinates in the events was the actual path taken by the rider. Empirical cumulative distribution function (ECDF) plots and Kolmogorov-Smirnov tests indicated 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. 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 reduction in transitions onto sidewalks when riders were on feedback-enabled scooters. This suggests that feedback mechanisms can be valuable tools in guiding e-scooter riders' decisions on where to ride, potentially reducing conflicts between pedestrians and scooter riders.

17. Key Words		18. Distribution Statement No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161. http://www.ntis.gov	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 36	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page author

Evaluating the Effectiveness of Computer Vision Systems Mounted on Shared Electric Kick Scooters to Reduce Sidewalk Riding

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Executive Summary

The objective of this study was to assess the efficacy of using auditory feedback and speed limitations on shared e-scooters equipped with computer vision sensors to reduce sidewalk riding... To do this, we used data provided by Spin, a US-based micromobility company, on Santa Monica e-scooters that were equipped with a computer vision system to monitor surface type. We conducted an experiment in which 50 e-scooters had their feedback mechanisms for sidewalk riding turned off, while another 50 had them turned on. The study was conducted from November 23, 2022 to February 14, 2023, during which time 488 trips were made within the city of Santa Monica, California. We analyzed the data by calculating the time and distance between consecutive changes in the riding surface within a trip, and using the straight-line distance between two GPS coordinates as a proxy for the distance of the actual path taken by the rider.

Empirical cumulative distribution function (ECDF) plots and Kolmogorov-Smirnov tests indicate that feedback from the computer vision system 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, 26% less distance on sidewalks, and 5% more time on streets 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.

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Section 1 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. 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 how to adopt new regulations and guidelines that 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 utilized 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 D.C [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].

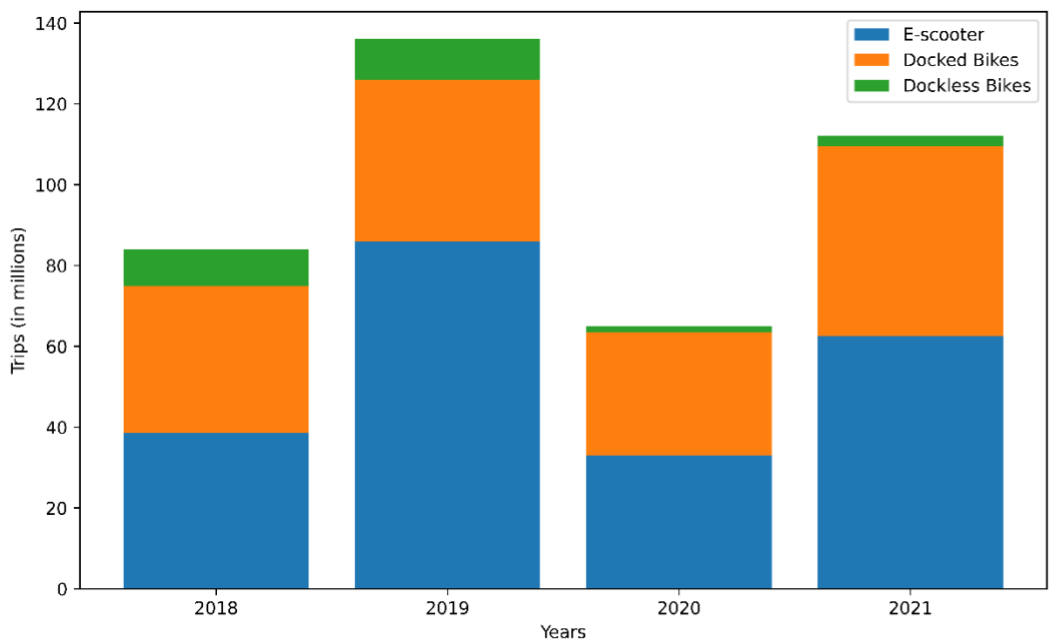

Figure 1: Number of trips made by each shared micro mobility modes from 2018 to 2021.

Data sourced from NACTO 2018,2019,2022 [3]–[5]

Section 2 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, multiple researchers have found that the use of e-scooters is commonly observed in areas with high employment rates and existing bicycle infrastructure, similar to the findings of various bikesharing studies. 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 blind or 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. 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].

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 when bike lanes are unavailable. 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 when narrow 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 cities and states. Even though sidewalk riding is prohibited in Salt Lake City, Badeau [13] found that 44% of patients involved in e-scooter-related crashes (22 out of 50) reported their crash had occurred on a sidewalk. When deciding where e-scooters should be allowed, policymakers should consider the seriousness of injuries that occur on the road versus sidewalks, as well as the potential conflicts arising from sharing sidewalks with pedestrians [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 encompass the establishment of specialized infrastructure, utilization of signage and signals, adoption of traffic calming measures, and implementation of the complete street principle to promote alternative modes of transportation in lieu of motor vehicles. Studies have shown that vegetation and road signage can affect the minimum sight 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 [29, 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 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. 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 [38]. 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 [39].

Section 3 Study, Experiment and Survey Design

This work evaluates an intervention that sits at the nexus of infrastructure, vehicle, and behavioral strategies. Shared e-scooters in Santa Monica, CA were equipped with hardware and software that monitors the vehicle's riding location and encourages riders to ride in legal locations. Unlike GPS-based technologies, which are unreliable for detecting sidewalk riding because of limits on precision [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.

Spin, a micromobility company based in the United States, deployed 100 such scooters in Santa Monica in late 2022. Although the primary objective 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 streets, bike lanes and sidewalks, thanks to the AI camera capacity to detect the type of surface traveled upon. Riding on sidewalks is prohibited in Santa Monica. Whenever the rider entered a sidewalk, a combination of feedback alerts and speed limitation were 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. These feedbacks and limitations persisted unless the rider exited 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 in to 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 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.

We designed two surveys to gain insight into the underlying factors that contribute to sidewalk riding. After riders completed their trip, Spin sent them an email requesting that they complete one of the two surveys, depending on whether they were in the feedback or no-feedback group. We used Google Forms to implement the survey, and to ensure the privacy and anonymity of respondents, we did not link any personal information such as email addresses or Spin user IDs to their respective trips. To incentivize riders to complete the survey, we offered a $3 Spin credit promo code to those who provided their email address in a separate survey document. The table below displays the survey questions and the corresponding groups to which these questions were presented. It is worth noting that the survey was interactive. For instance, if a respondent in the feedback group indicated that they did not ride on sidewalks except at the start and end of their trips, the questions relating to their reasons for sidewalk riding and their reaction to feedback were not presented to them.

Table 1: Survey Questions and Group Assignment

Number	Question	Available Options	Group Asked
1	Other than at the start and end of your trip, did you ride on the sidewalk during the trip you just completed?	• Yes • No	Both

2	What was your main reason for riding on the sidewalk?	• I felt safer than riding on the street or bike lane. • It was more convenient to ride on the sidewalk. • It was faster than riding on the street. • I was following somebody who went on the sidewalk. • I didn't ride on the sidewalk.	Both
3	Did your Spin scooter slow down or make sounds when you rode on the sidewalk?	• Yes • No	Feedback
4	Did you move off the sidewalk when the scooter slowed and alerted you?	• Yes • No	Feedback
5	Did the slowing and alerts on the sidewalk make you more or less likely to use Spin scooters in the future?	• More likely to use Spin scooters. • Less likely to use Spin scooters. • Neither more nor less likely	Feedback
6	What are the City of Santa Monica rules regarding Spin scooters on sidewalks?	• It's allowed so long as you don't bother pedestrians. • It's allowed if there is not a bike lane available on the street. • It's not allowed.	Both

7	How did you learn about the rules regarding sidewalk riding?	• The Spin app • I rode a Spin scooter before this trip, and it slowed and alerted me when I was on the sidewalk. • I read the city's website. • Other	Both

Section 4 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, and the surface change is recorded as an "event". 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 23rd, 2022, to February 14th, 2023, the time during which the sample 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 2 shows the summary statistics of the data.

Table 2: Summary Statistics of the Data

	Number of Trips	Trip time (Minutes)		Origin-Destination Distance (km)	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Feedback	289	12.0	13.5	1.0	1.0
No Feedback	167	13.4	14.1	1.0	0.9

We employed the Euclidean distance formula to calculate the distance between two successive events in a trip based on their coordinates. Figure 2 displays the distribution of the Euclidean 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 distance between two consecutive events corresponds to the path taken by the rider. Figure 2 shows that the median distance between consecutive events is 33 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.

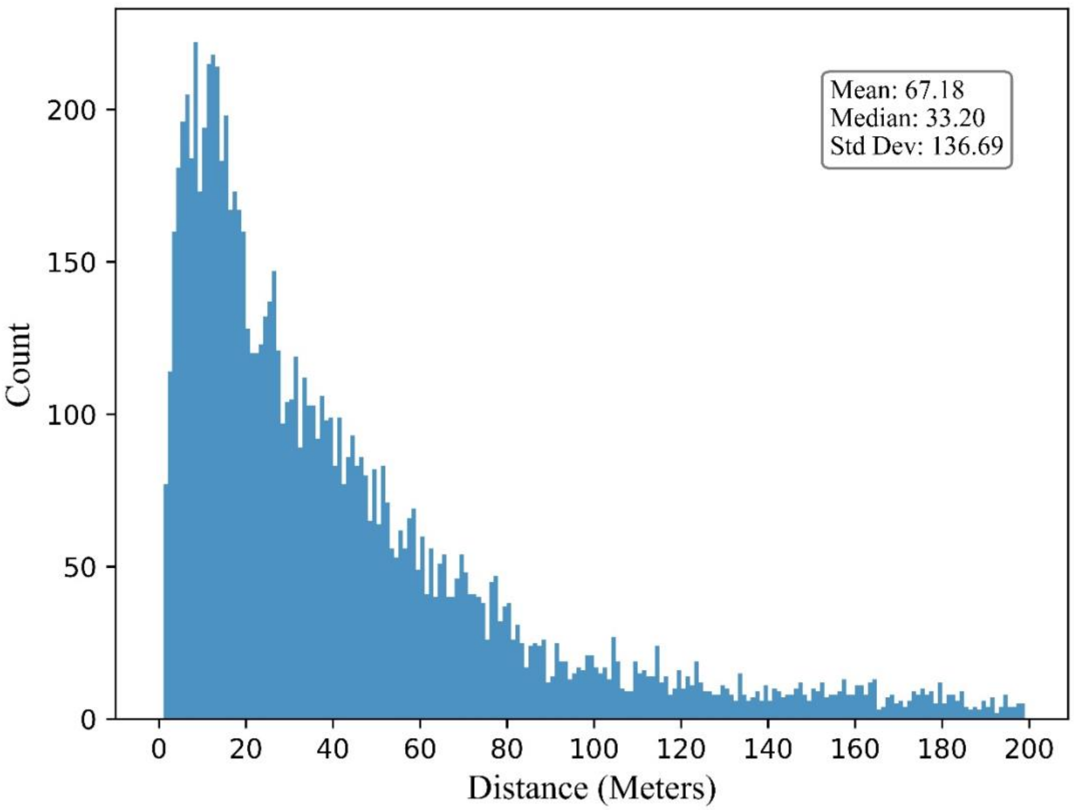

Figure 2: Histogram of Euclidean Distance Between Consecutive Events Within a Trip

Section 5 Methods

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 in 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.

Additionally, 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.

Section 6 Results

To evaluate the difference among feedback and no-feedback group, 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.

Subsection 6.1 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. Summary statistics for total time and distance on each surface are shown in table 3.

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 highly significant reduction in both the length and duration of individual segments of sidewalk riding.

Table 3: Individual-event Level Segment of Time and Distance on Each Surface Statistics

Surface	Measure	Feedback			No feedback		
		Mean	Std. Dev.	Number of events	Mean	Std Dev	Number of events
Sidewalk	Time (Seconds)	31	161	635	31	95	631
	Distance (Meters)	35	73		45	74	
Street	Time (Seconds)	22	49	1831	22	48	1486
	Distance (Meters)	79	171		79	186	
Bike lane	Time (Seconds)	10	14	1263	10	15	963
	Distance (Meters)	51	62		52	60	

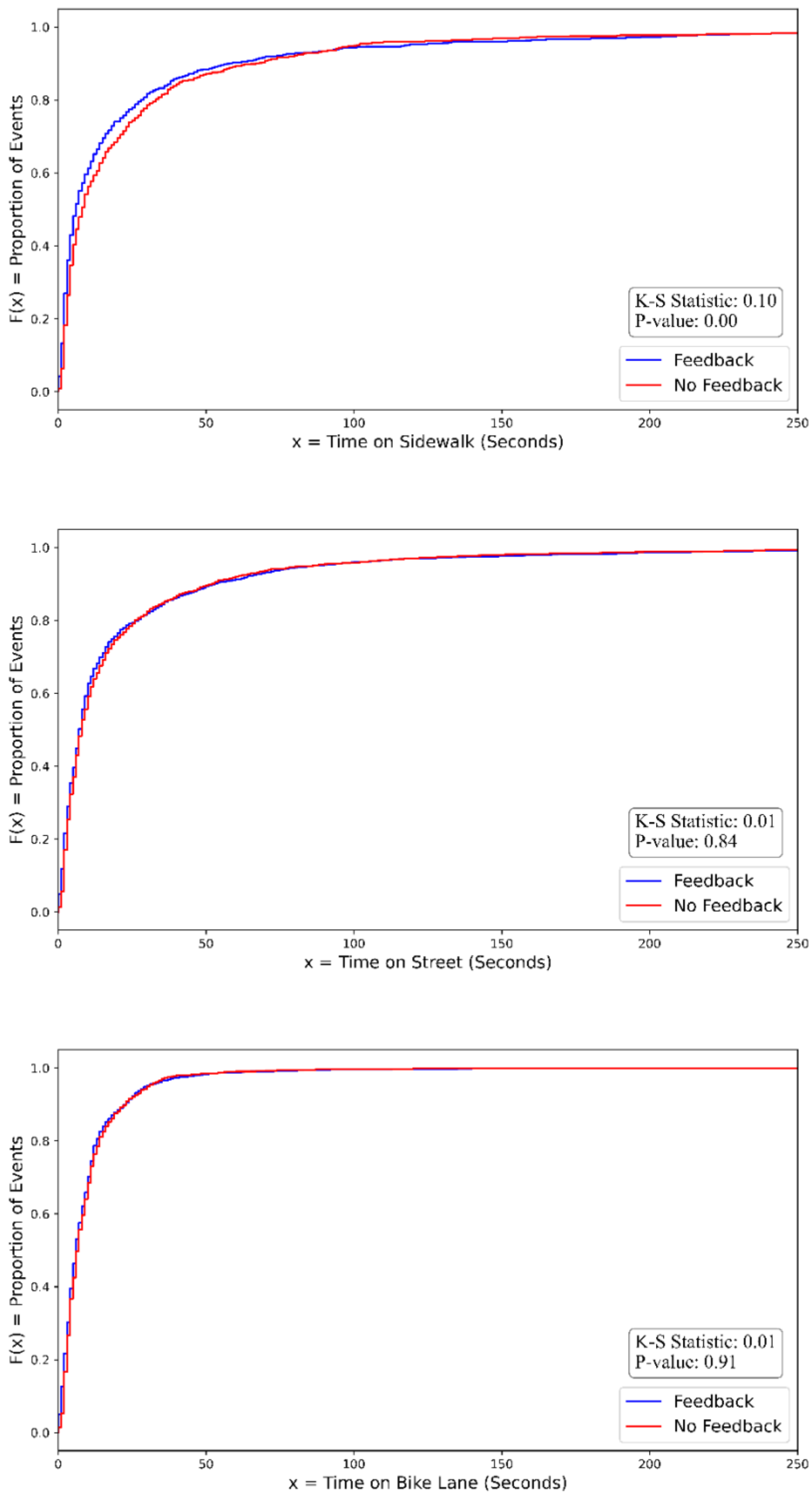

Figure 3: ECDFs of Individual-event Level of Time Ridden on Each Surface Type for Feedback and No-feedback Groups

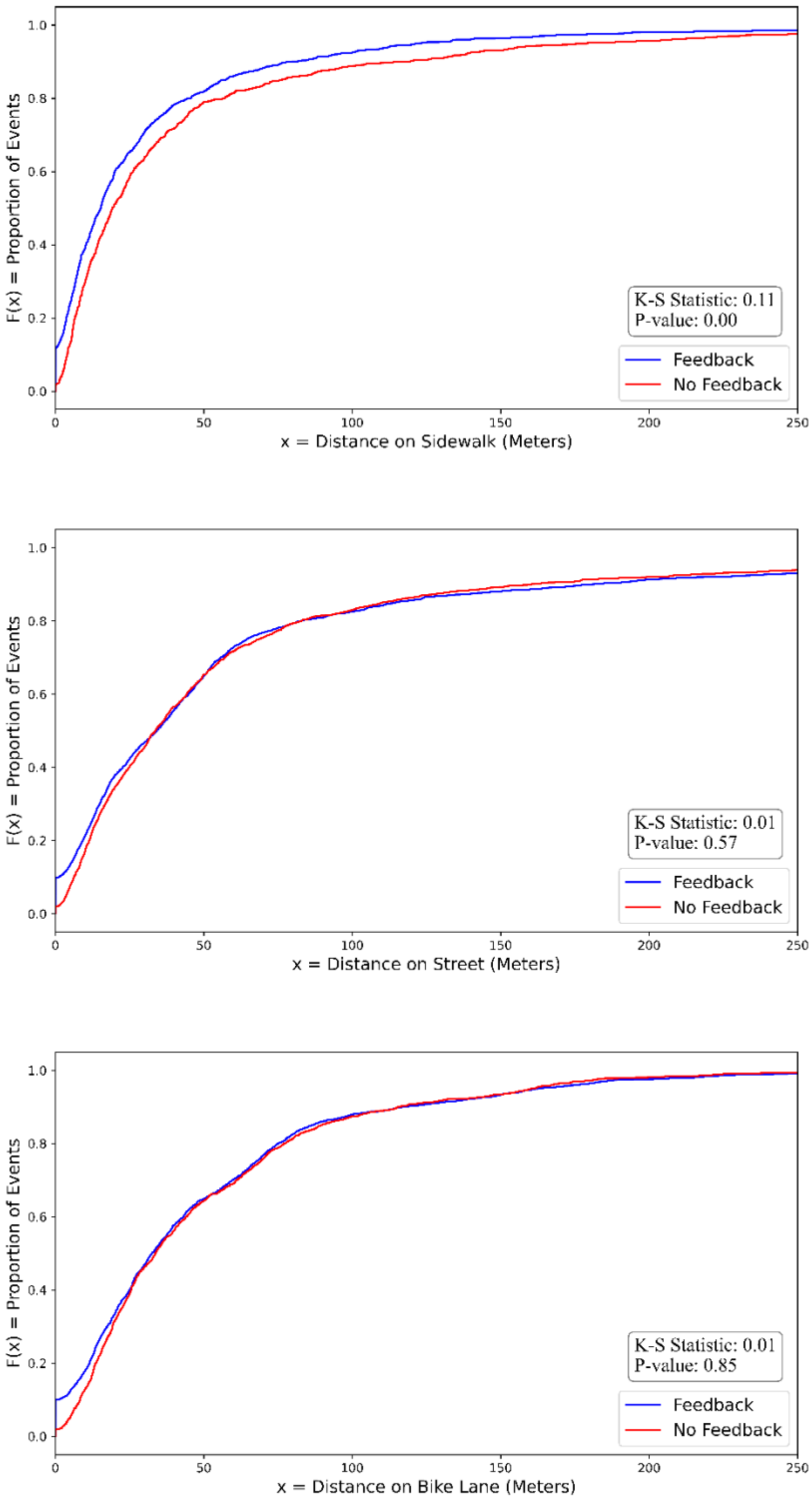

Figure 4: ECDFs of Individual-event level Segment of Distance Ridden on Each Surface Type for Feedback and No-feedback Groups

Subsection 6.2 Trip-level Fraction of Time and Distance on Each Surface

To adjust for any potential differences in individual events 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. Table 4 shows the summary statistics for the fractions of time spent on each surface, by group.

Table 4: Trip-level Fraction of Time and Distance Summary Statistics

Surface	Measure (Fraction of)	Feedback		No-feedback	
		Mean	Std. Dev.	Mean	Std. Dev.
Sidewalk	Time	0.17	0.24	0.22	0.26
	Distance	0.11	0.19	0.15	0.22
Street	Time	0.59	0.25	0.56	0.25
	Distance	0.61	0.24	0.56	0.25
Bike lane	Time	0.22	0.21	0.22	0.21
	Distance	0.27	0.23	0.28	0.24

The corresponding ECDF plots for time and distance are shown in Figures 5 and 6 respectively.

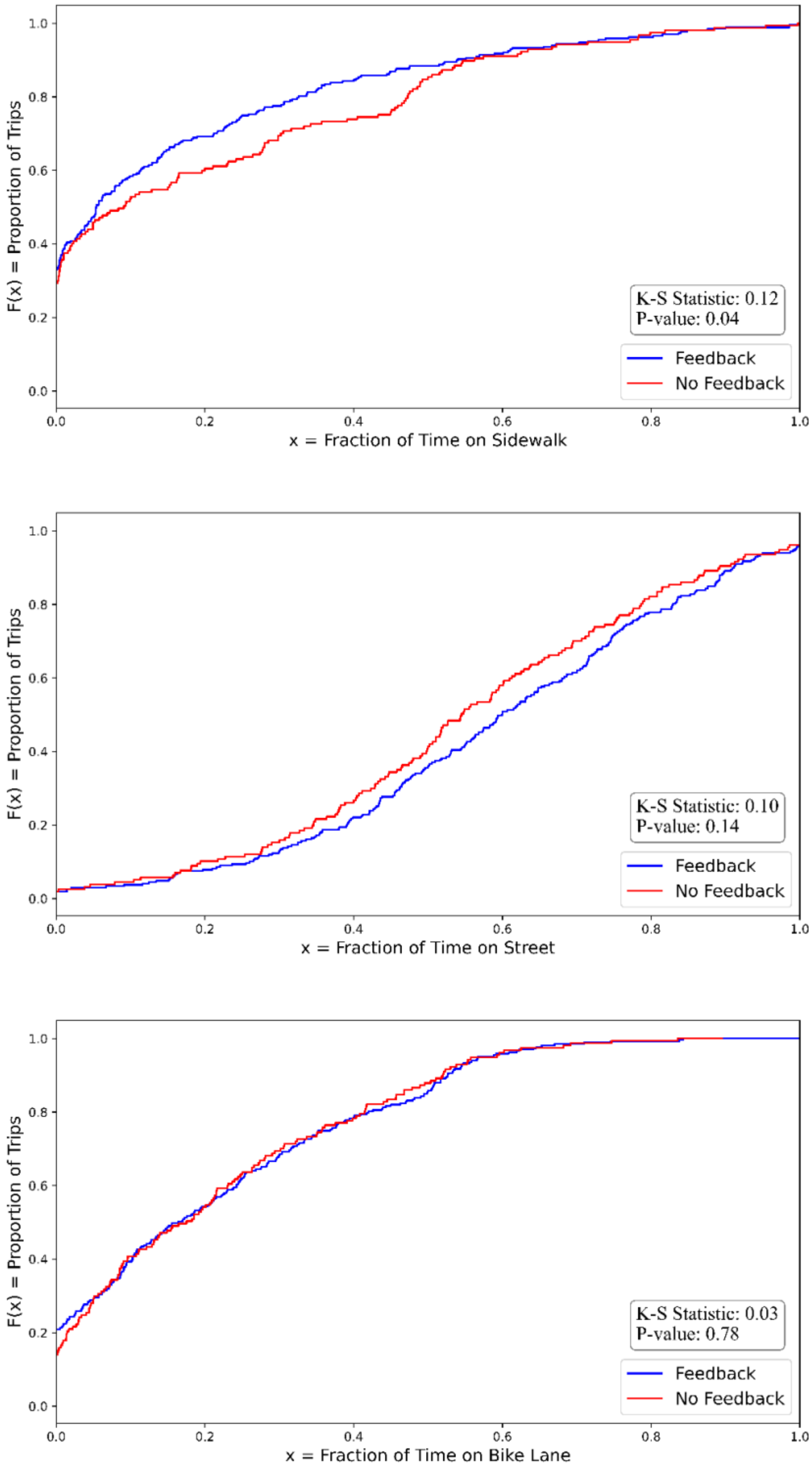

Figure 5: ECDFs of Fraction of Time Ridden on Each Surface Type for Feedback and No-feedback Groups

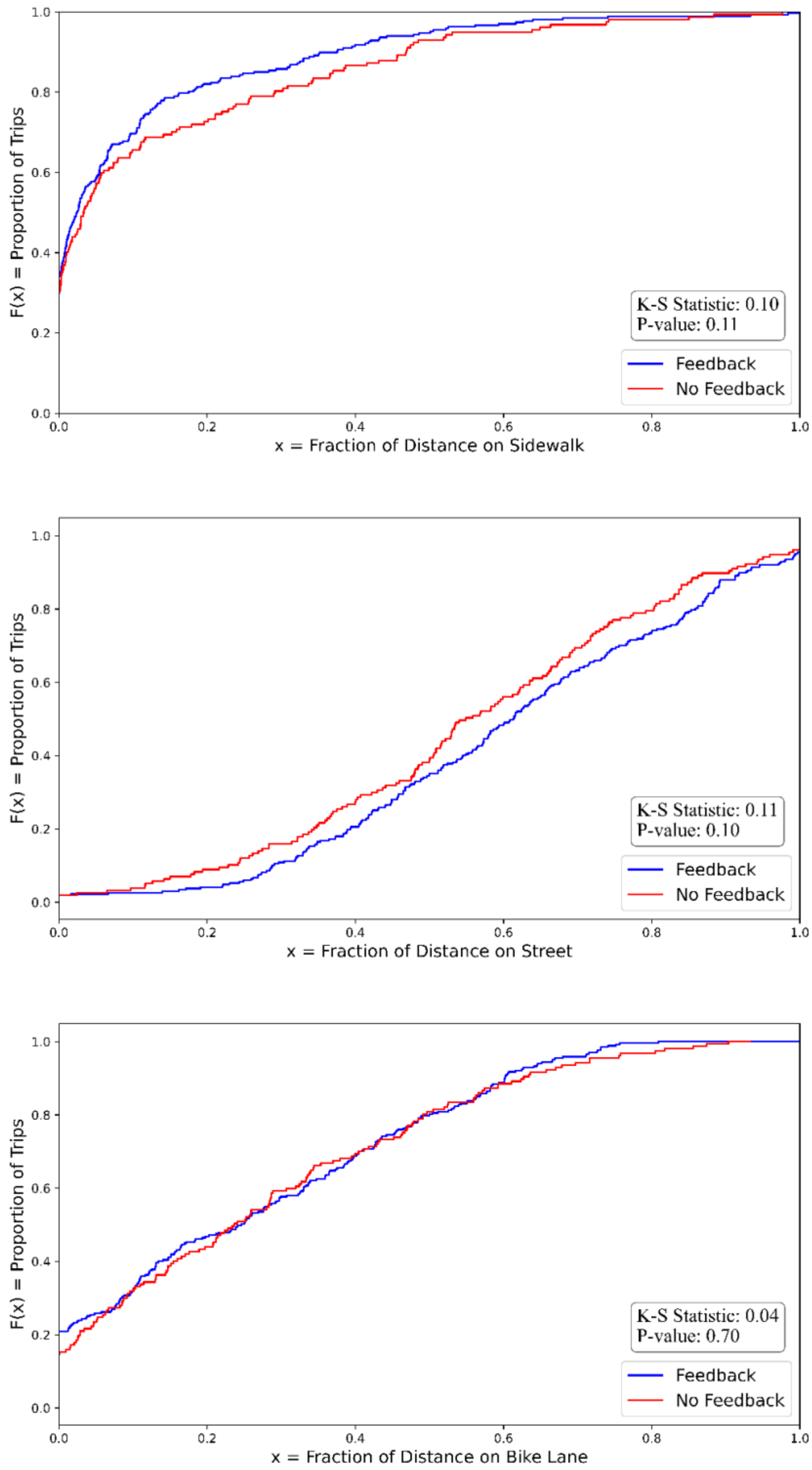

Figure 6: ECDFs of Fraction of Distance Ridden on Each Surface Type for Feedback & No-feedback Groups

Subsection 6.4 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 every trip. Summary statistics for total time and distance on each surface are shown in Table 5.

Figures 7 and 8 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 and distance traveled on sidewalks, but these shifts are significant only at the 0.1 level.

Table 5: Trip-level Total Time and Distance Summary Statistics

Surface	Measure	Feedback		No-Feedback	
		Mean	Std. Dev.	Mean	Std. Dev.
Sidewalk	Time (Seconds)	132	396	160	297
	Distance (Meters)	149	355	229	456
Street	Time (Seconds)	261	317	280	345
	Distance (Meters)	945	1124	998	1077
Bike lane	Time (Seconds)	83	118	88	130
	Distance (Meters)	421	556	436	572

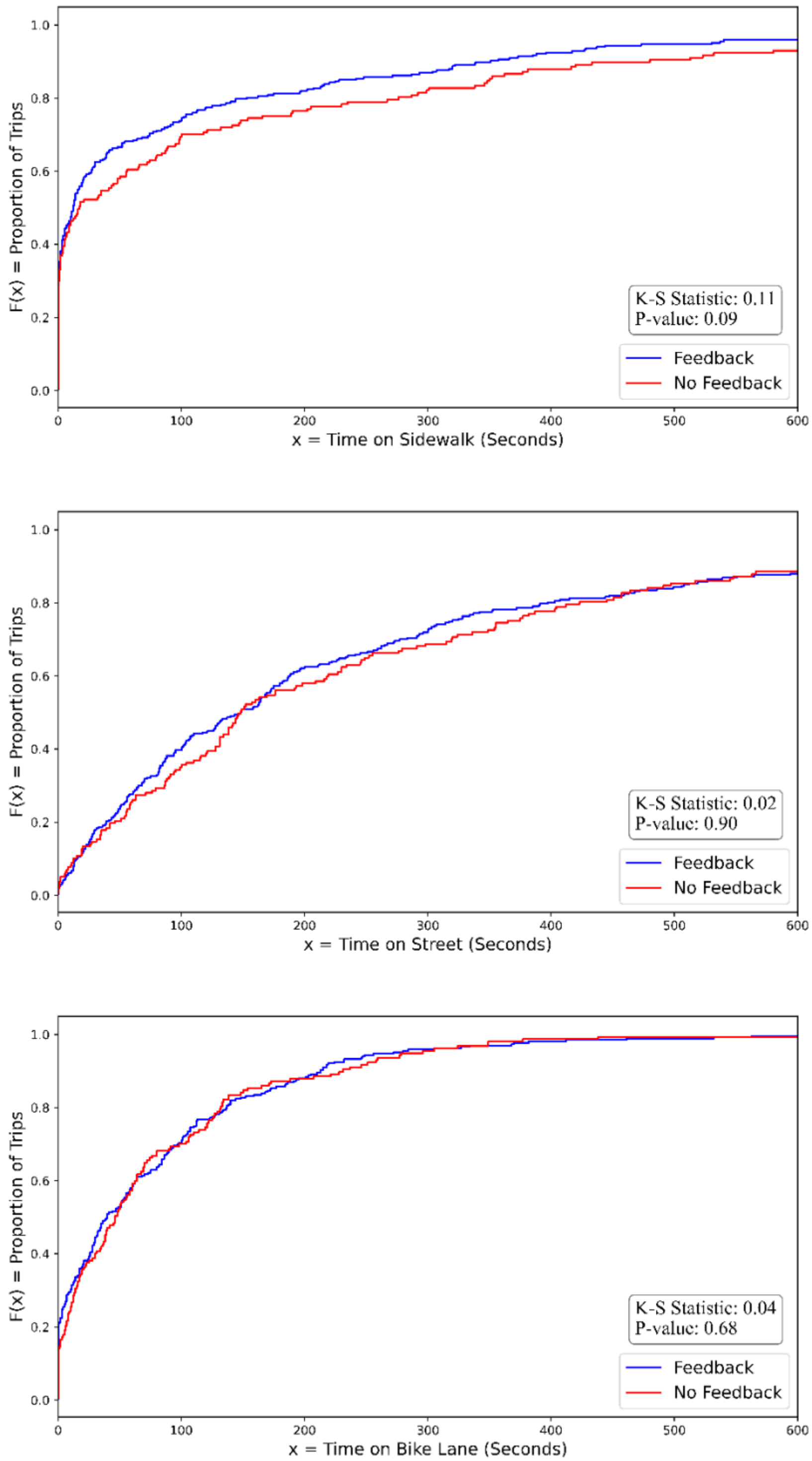

Figure 7: ECDFs of Trip-level Total Time Ridden on Each Surface Type for Feedback and No-feedback Groups

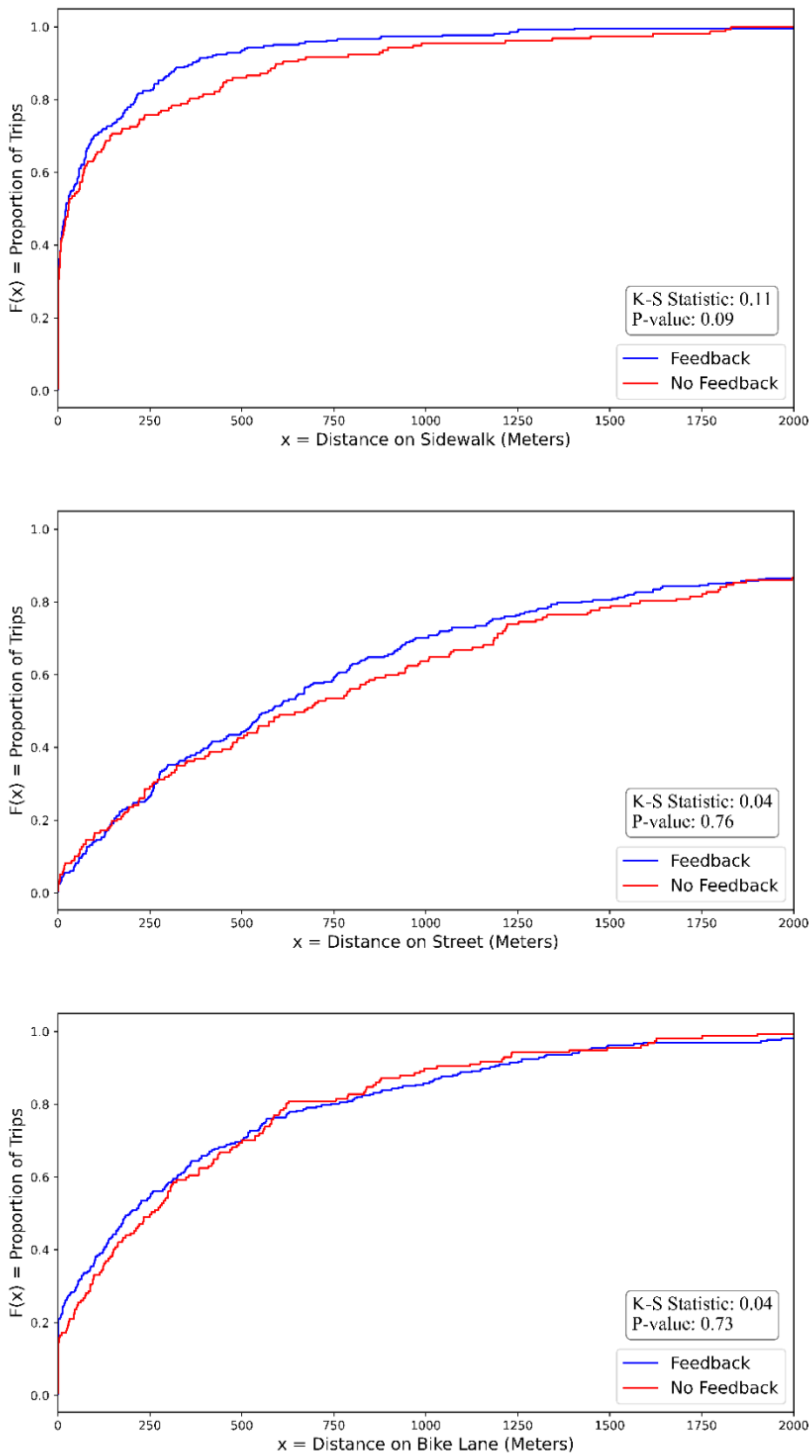

Figure 8: ECDFs of Trip-level Total Distance Ridden on Each Surface Type for Feedback and No-feedback Groups

Subsection 6.5 Markov State Transition Diagram

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. Tables 6 and 7 report the state transition matrices for the feedback and no-feedback groups, respectively. 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.

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.

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

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 data is from the feedback group, and 0 otherwise. β_0 is the intercept and β_1 is the coefficient of the dummy variable. Table 8 shows the logistic regression results for transition states starting from street.

Table 6: State Transition Matrix for Feedback Group

From \ To	Street	Sidewalk	Bike Lane
Street	0	0.32	0.68
Sidewalk	0.88	0	0.12
Bike Lane	0.96	0.04	0

Table 7: State Transition Matrix for No-feedback Group

From \ To	Street	Sidewalk	Bike Lane
Street	0	0.38	0.62
Sidewalk	0.89	0	0.11
Bike Lane	0.94	0.06	0

Table 8: Logistic Regression Result for Transition States with Street as the First Event

Coefficient	Estimate	Std. Err	Z	*p*	95% CI	
					2.5 %	97.5%
β_0	-0.589	0.048	-12.230	0.000	-0.684	-0.495
β_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 coefficient (β_1) of less than zero suggests 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 9 shows the logistic regression results for transition states starting from bike lane.

Table 9: Logistic Regression Result for Transition States with Bike Lane as the First Event

Coefficient	Estimate	Std. Err	Z	*p*	95% CI	
					2.5 %	97.5%
$\boldsymbol{\beta_0}$	-2.671	0.113	-23.681	0.000	-2.893	-2.451
$\boldsymbol{\beta_1}$	-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

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.

Subsection 6.6 Survey Results

Spin sent an invitation to complete a short survey to all users of the AI-equipped scooters (including the feedback and no-feedback groups) during the study period. The corresponding survey forms for each group were sent to users based on the type of scooter they used. The survey yielded a total of 44 responses, representing approximately a 10% response rate. Responses were evenly distributed between the groups that received feedback and those that did not. The survey results are presented in Tables 10 and 11. In the feedback group, 68% of respondents stated that they did not ride on sidewalks except at the start and end of their trip. This finding was similar to that of the no-feedback group, in which 64% of respondents gave the same answer. Among the 22 respondents who reported receiving feedback, seven reported that they had ridden on sidewalks for reasons other than the start and end of their trip. Their responses regarding the reasons for sidewalk riding are presented in Table 8. Due to the limited sample and subgroup sizes, we did not undertake any statistical analysis of these data.

Table 10: Survey Results Questions Among Feedback and No-feedback Groups

Questions	Options	No-feedback Group	Feedback Group
Other than at the start and end of your trip, did you ride on the sidewalk during the trip you just completed?	Yes	8 (36%)	6 (29%)
	No	14 (64%)	15 (71%)
What was your main reason for riding on the sidewalk?	I felt safer than riding on the street or bike lane	2 (29%)	1 (17%)
	It was more convenient to ride on the sidewalk	0 (0%)	2 (33%)
	It was faster than riding on the street or bike lane	1 (14%)	0 (0%)
	I was following somebody who went on the sidewalk	2 (29%)	0 (0%)
	I didn't ride on the sidewalk	2 (29%)	1 (17%)

	Other (Bike Lane occupied, Scooter was parked on sidewalk.	0 (0%)	2 (33%)
What are the City of Santa Monica rules regarding Spin scooters on sidewalks?	It's not allowed	14 (70%)	15 (75%)
	It's allowed if there is not a bike lane available on the street	5 (25%)	4 (20%)
	It's allowed so long as you don't bother pedestrians	1 (5%)	1 (5%)
How did you learn about the rules regarding sidewalk riding?	The Spin app	9 (43%)	12 (63%)
	I rode a Spin scooter before this trip, and it slowed and alerted me when I was on the sidewalk	3 (14%)	3 (16%)
	I read the city's website	8 (38%)	3 (16%)
	Others: (I guessed; I keep up with Santa Monica news)	1 (5%)	1 (5%)
Did you move off the sidewalk when the scooter slowed and alerted you?	Yes	NA	2 (33%)
	No	NA	4(67%)
Did your Spin scooter slow down or make sounds when you rode on the sidewalk?	Yes	NA	6 (86%)
	No	NA	1 (14%)
Did the slowing and alerts on the sidewalk make you more or less likely to use Spin scooters in the future?	More likely to use Spin scooters	NA	0 (0%)
	Neither more nor less likely	NA	2 (34%)
	Less likely to use Spin scooters	NA	4 (66%)

Table 11: Survey Results of Feedback Group on Reasons for Riding on Sidewalks

	Reasons for Sidewalk Riding					
Options	I felt safer than riding on the street or bike lane	It was more convenient to ride on the sidewalk	It was faster than riding on the street or bike lane	I was following somebody who went on the sidewalk	I didn't ride on the sidewalk	Other
Response (percent)	1 (16%)	2 (33%)	0 (0%)	1 (16%)	1 (16%)	1 (33%)

Conclusion

Directionally, the results of this work indicate that the total time and distance, and the proportion of time and distance, traversed on sidewalks was lower for the feedback group than for the no-feedback group. For total time and distance, the difference was significant at the 0.1 level. For the proportion of time, the difference was significant at the 0.05 level, while the difference in proportion 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 26% 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 an 8% 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.

By analyzing the ECDF plots, we can gain a deeper understanding of the riding behavior within each group. For instance, in Figure 5, it is apparent that nearly half of riders spend less than 10% of their time riding on sidewalks, even when feedback was disabled. At the same time, about 1 in 10 trips 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 the majority 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 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. To address this issue, Spin decided to remove all camera-equipped scooters from service. As a result, the number of recorded trips decreased, 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.

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