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E-scooters and public transit: unveiling the conditions for a connection using trip and survey data

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ABSTRACT

Shared e-scooters have become a popular alternative for short trips and can serve as a first- and last-mile connector to transit. This study investigates the factors motivating e-scooter users to connect to public transit through the analysis of 48,301 e-scooter trips in 20 US cities. While most e-scooter studies, to date, rely on geospatial assumptions to assess whether a transit connection was made, this study uses rider survey data where users reported transit connections upon ending their e-scooter trip. Presented during the parking process, the rider survey asked when the decision to use the e-scooter was made. Responses were analyzed using a binary logit model on the decision to use e-scooters in connection to transit. The model includes urban and built environment characteristics to control for heterogeneity across urban spaces. People who decide to use an e-scooter spontaneously are found to be more likely to connect to transit than those who plan their trip in advance. This research provides novel insights into modal substitution, demonstrating how an e-scooter trip may substitute for just a portion of a transit trip rather than the full trip. Respondents were segmented into four groups based on their propensity for connecting with public transit: complements (20.5%), substitutes (3.2%), no interaction (72.9%), and mixed effects (3.3%). Trips that substituted for transit averaged 1.82 miles, a statistically significant longer distance than those complementing transit trips or that had no transit interaction. We conclude that these trips may otherwise have been made by rideshare, and previous assessments have overestimated the modal substitution of e-scooters for transit. Among the 6.5% of trips for which respondents say they would have used transit if e-scooters were not available, approximately half connected to transit before/after using the e-scooter, suggesting a more nuanced adjustment in how e-scooters complement the use of transit.

1. Introduction

The first shared e-scooters appeared on the streets of Santa Monica, California in September 2017. Within a year of their introduction, this new form of micromobility was already operating in 65 cities across the US (Irfan, 2018), and its popularity continued to steadily grow reaching 86 million annual rides in the country in 2019. The onset of the COVID-19 pandemic led to a dramatic decline in shared e-scooter trips, falling to about 32 million (Shared Micromobility in the US and Canada: 2022, 2022). By 2022, while annual trips had risen to 57 million, ridership had not recovered to its pre-pandemic levels. In 2023, trip volumes reached an all-time high of 172 million (NABSA, 2024). The number of systems with e-scooters has steadily increased year-over-year, rising from 151 in 2019 to 265 in 2023 (NABSA, 2022; NABSA, 2023). The use of shared e-scooters has been often considered an attractive way to promote alternatives to driving over short distances (at least in North American cities, see the discussion in (Wang et al., 2023)). According to 2022 US National Household Travel Survey (NHTS) data, 39 % of trips were under 3 miles, of which 63.4 % were made by automobiles (cars, SUVs, taking a taxi and/or ride-hailing services). While at least a portion of these short

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trips could not be made with other means of travel alternative to the use of cars (e.g. short trips that are part of a longer *tour* for which a car is required), there is potential for some mode shift for at least some of these trips. E-scooters and other micromobility options could play a crucial role in supporting this shift away from cars, including when used as a first-/last-mile service to expand the catchment area of public transit.

The inquiry into whether and how shared e-scooters stimulate transit use holds crucial significance for urban policy. Existing evidence suggests that e-scooter usage not only substitutes for private car and ride-share trips but also impacts trips on public transit (Meroux et al., 2022; Wang et al., 2023). E-scooters can also be a complementary mode to public transit, serving as a first- and last-mile connector mode, but usage patterns vary greatly by city, in terms of the type of users, locations where first/last access trips are observed, and the volume of trips (Bai and Jiao, 2020; Li et al., 2022). Many studies have attempted to assess mode substitution and complementarity patterns; however, a notable gap in understanding persists concerning the reasons and circumstances influencing individuals to use e-scooters as an access mode for connecting to transit. This study addresses this research gap.

Our research investigates the factors that influence the interactions between the use of shared e-scooters and public transit. While most e-scooter studies, to date, rely on geo-spatial assumptions to assess whether a transit connection was made, this study uses rider survey data where users reported transit connections immediately upon ending their e-scooter trip. It explicitly asks respondents if they connected to transit before or after using the e-scooter. The unique data collection approach affords us valuable insights into the nuanced interplay between these two modes of transportation. In line with Yang et al. (2025), this survey also represents an exploratory research into the users' decision-making process for using an e-scooter. Riders were asked how far in advance of their trip they decided to use the e-scooter. Through multivariate analysis, we explore how the likelihood of e-scooter users connection to transit is explained by these factors. We find that when the user planned to use an e-scooter, travel time, the reason for choosing to use an e-scooter, built environment characteristics such as population and employment density of the locations where the trip was made and the time of day when the trip was taken are all significant explanatory factors for e-scooter trips connecting to transit.

Our study contributes to the literature in two main dimensions. First, using a large dataset consisting of trip-level and survey data from multiple cities across the United States, while controlling for built environment characteristics, we investigate the conditions under which an e-scooter trip is likely to involve a transit connection, given that someone decides to take an e-scooter trip. This approach helps assess which e-scooter trips are likely to connect to transit, based on location, trip duration, time of day, motivating factors and when the decision to use an e-scooter was made. Second, the study enhances the understanding of the extent to which e-scooters substitute or complement the use of transit. This interaction, which is often not fully understood, is clarified in our study through novel evidence suggesting that users who claim to replace transit trips with e-scooters often also report connecting with transit on the same trip. This means a more complex form of intermodality, where e-scooter users may substitute for a segment of their transit trip but ultimately still connect to transit for the remaining portion of the trip. This study is crucial for understanding how trip-level features and built environment characteristics can be sources of heterogeneity in people's decisions to integrate shared e-scooters with public transit.

The remainder of this paper is structured as follows: the next section provides a *literature review* on the existing research about shared e-scooter use and whether e-scooter trips are found to substitute or complement transit and their scope as a first-and-last mile connection for transit trips. The following section provides details and insights about the *data and methods* we have used. In the next section, we describe *results and discussion,* where we share estimates of the model and their interpretations. Finally, the last section discusses the *conclusions* of our research, where we discuss key takeaways, limitations and the future direction in this field of research.

2. Literature review

Shared e-scooters are found to have either substitution or complementary effects on existing travel demand patterns at both the individual and societal levels. Current studies attempted to understand the factors affecting the usage of shared e-scooters based on two approaches: 1) analyzing the spatiotemporal patterns of shared e-scooters using data collected in different geographic contexts; 2) conducting behavioral surveys to explore who are more likely to ride shared e-scooters and capture the impacts of shared e-scooters on the use of other transport modes. Studies suggest that the factors influencing the use of shared e-scooters are similar to other shared micromobility services, i.e., station-based and dockless bikesharing. For example, travel distance is one of the most important influential factors determining the rate at which the bicycle is a feeder mode to the metro (Chen & Cheng, 2016; Ma et al., 2018). One study using Sacramento, California as a case study area shows that middle- and high-income individuals, and students are more likely to use bike-share to connect to transit (Mohiuddin et al., 2023). Another study highlighted how female, older, and low-income transit commuters are less likely to use bikeshare to access metro services than their counterparts (Ji et al., 2018). Through market segmentation of bike-share users, Mohiuddin et al. (2024) show a segment of users who are mainly transit users and frequently use bike-share to connect to transit. Wang et al. (2023) provide a relatively up-to-date review of the literature for modal shifts associated with the use of shared e-scooters and report that the substitution rate of riding e-scooters instead of making auto trips averages 25–40 % of e-scooter trips. Moreover, the literature shows huge differences between geographic contexts, with public transit being more often replaced by the use of e-scooters in European countries (where the mode share of transit is higher). Instead, studies based on the analysis of behavioral survey data reveal that public transit trips are not likely to be replaced by e-scooter rides in most cities in the US (with only 3–18 % of e-scooter trips replacing the use of transit), also due to the limitedness of public transit services in many US locations. However, in cities where public transit is more commonly used, compared to the US average, the substitution rates of e-scooters with transit can be up to 34 %. Guo and Zhang (2021) highlighted how survey results from various cities show that shared e-scooters have great promise for replacing auto trips. For example, 48.6 % of shared e-scooter trips would have been completed using a private vehicle if shared e-scooters were unavailable in Portland (Guo and Zhang, 2021; PBOT, 2018); this value is 42.6 % in Chicago (City of Chicago, 2020; Guo and Zhang, 2021).

Previous studies have shown how bikeshare users tended to be young, wealthy, white males, but e-scooters attract a higher proportion of low-income and minority riders (Beale et al., 2022). Many geospatial analyses conducted in Europe and America (Bai & Jiao, 2020; Caspi et al., 2020; Lu et al., 2021; Zhu et al., 2020) find that shared e-scooter trips in general are usually not used for commuting, and access to public transit is positively associated with higher shared e-scooter usage (Bai & Jiao, 2020). One recent study reported that approximately one third of shared e-scooter trips in Indianapolis could compete with bus service and were concentrated in the local downtown. However, another third were complementary trips, and these trips primarily happened outside downtown (Luo et al., 2021). Conversely, another study conducted in Austin found a positive association between shared e-scooters and transit in the downtown area, but a negative relationship outside (Lu et al., 2021). The results of these two studies suggest that shared e-scooters may have a positive or negative impact on public transit ridership, depending on local circumstances. Another group of studies relied on behavioral surveys and summarized the influence of factors such as gender, age, income, education background, residence status, attitudes toward road infrastructure, trip purposes, trip distance, and duration, and temporal patterns (Wang et al., 2023). There were mixed results from these surveys, which warrant further investigation.

Several European studies suggest that shared e-scooters have a greater displacement effect on public transit trips than their counterparts in North America (Li et al., 2022). There can be multiple reasons for this finding, as public transit trips account for a smaller proportion of total trips in the US, and they are typically longer than public transit trips in European cities. A city-level understanding of shared e-scooter substitution effects would be desirable. A study conducted in three French cities showed that e-scooters are preferred over public transportation due to their rapidity and ability to travel door-to-door (Krier et al., 2019), suggesting they often substitute for public transit for this reason. Despite this, the report also showed that more than half of shared e-scooter return trips are made by public transportation. Another study found that 28 % of respondents to an e-scooter user survey would not have taken public transit without shared e-scooters (Powered Scooter Share Mid-Pilot Evaluation, 2018). Luo et al. (2021) found complementarity of 29 % of shared e-scooter trips in Indianapolis with public transport and a competing relationship for approximately 27 % of the trips. Yan et al. (2021) estimated that one out of ten shared e-scooter trips complements the metro service of Washington DC (Kalakoni et al., 2024). This shows that e-scooter and transit integration tends to vary significantly across cities.

Our study fills several gaps in the literature. Modal substitution ought to be carefully analyzed, especially in the case of public transit, as what may seem like pure substitution may actually be more accurately described as complementarity when looking at the complete picture of a trip, or the complete tour made by the traveler. For example, the use of an e-scooter may replace a one-way trip via transit to a certain location, but if the trip back is made by public transit, then the two modes may be complementing each other. Our study focuses on this type of intermodality between shared micromobility and public transit, wherein a substitution of a transit trip by an e-scooter may not be a pure substitution as several users report both substituting and connecting to public transit via the e-scooter. This type of behavior suggests the complexity with which the two modes may be interacting.

Our study draws on a nationwide survey to offer new insights into how the built environment, trip-level characteristics, and individual motivations influence the complementarity between e-scooters and public transit. While previous research has primarily focused on land use and temporal factors (Javadiansr et al., 2024), limited attention has been given to user perceptions and personal reasons for choosing e-scooters. By integrating trip-level data, built environment metrics, and survey responses, our analysis helps fill this gap and contributes to a more comprehensive understanding of e-scooter–transit integration. Moreover, most studies are based on data from one or two cities (Yan et al., 2023; Javadiansr et al., 2024; Lu et al., 2024; Zuniga-Garcia et al., 2022). Our dataset spans 20 cities across the US and thus provides a more holistic depiction of e-scooter and transit integration.

Finally, most e-scooter studies rely on geo-spatial assumptions to assess whether a transit connection was made. This commonly used process of attributing shared e-scooter trips to specific transit routes can be misleading. Areas with high population density often have transit stops located in close proximity to each other. Assuming an e-scooter trip connects to public transit solely on the basis of its proximity to a transit stop risks overestimating how complementary the two modes really are. Moreover, some shared e-scooter trips can fall within the catchment areas of multiple routes, which can result in double counting (Ziedan et al., 2021). Our study is unique in the sense that we use rider survey data where users reported transit connections immediately upon ending their e-scooter trip. The survey explicitly asks respondents if they connected to transit before or after using the e-scooter.

3. Data and methods

The data used in the study was collected by the shared micromobility company Spin from July to November 2021 in 20 US cities (Fig. 1). The end-of-ride survey was deployed natively in the Spin app as a pop-up after the user parked their e-scooter. It was active in each city for approximately 30 days. No identifying or demographic data was collected, but respondents were asked to consent to the use of their GPS trip location data for research. Raw GPS data was processed to anonymize the exact locations to avoid identifying specific housing units or addresses (a problem, in particular, in lower-density neighborhoods with a small proportion of multi-family buildings). A total of 50,306 anonymized trip-level responses were collected. The dataset, including survey responses and trip data, was provided to UC Davis through a University research partnership sponsored by Ford Motor Company. Spin was acquired by Ford in November 2018 and sold to TIER Mobility in April 2022.

3.1. Survey Design

The end-of-ride survey instrument was jointly developed by e-scooter operator Spin and UC Davis. It was designed to be answered quickly, with only five questions, including consent. Question topics included 1) whether the users connected to transit either before or after the e-scooter trip, 2) motivating factors for using the e-scooter, 3) the timing of their decision to take the e-scooter, and 4) the alternative mode they would have used if the e-scooter were not available. Users were asked to report when they planned to take a trip by e-scooter, and responded by choosing among three options: *(1) spur of the moment (when I saw the scooter)*, *(2) shortly before starting the trip,* and *(3) planned earlier in the day or the days before*. Other answer choices and responses are shown in Table 2.

3.2. Dataset Used for Analysis

The dataset provided to UC Davis contains survey responses and trip-level characteristics such as distance travelled, start and end locations, duration of the trip, and time of day, along with user survey responses. This dataset was enriched with built environment characteristics such as population, employment, and intersection density of the locations where the trip was made. This multi-dimensional approach enhances the depth and robustness of our research findings.

After data cleaning, our dataset contains 48,301 complete survey and trip observations. Based on the speed of the trips, we made some observations that had implausible speed values, given that the fastest an e-scooter can go is 15 miles per hour in the US areas of service included in the study. We also excluded cases with distances shorter than 100 m and had a travel time of less than one minute. We assumed that these records did not represent a full trip to a separate destination, but rather a case in which there was a malfunctioning of the e-scooter that led to interrupting the trip, or the traveler interrupted their trip for other reasons before getting to their destination. The original sample consisted of 50,306 trips. 170 observations (0.338 % of the sample) were found to report speeds greater than 16 mph, and there were 1772 cases (3.52 % of the sample) with distances less than 100 m. 693 observations (1.38 % of the sample) were found to have trip times less than one minute. These cases were dropped from the sample; with 620 overlaps, our remaining sample consisted of 48,301 observations. The total cases that dropped constitute 4.15 % of the original sample. Each survey response was associated with trip data that the user just completed, including start and end timestamp and GPS coordinates, breadcrumb and crow fly distance, and trip duration. To protect user privacy, the e-scooter provider perturbed the raw GPS point coordinates prior to sharing the dataset for analysis. Each GPS coordinate was randomly deflected to a point within a 100-meter radius of the original point. This deflection may affect estimates of trip distances as well as other estimates. Anonymization methods introduce random noise in the data so that each location is perturbed in an unpredictable direction, producing measurement error. For trips shorter than 300 m, this deflection can produce

Fig. 1. Geographic distribution of survey sites across 20 US cities.

Table 1
List of cities where the end-of-ride survey was deployed, segmented by whether the e-scooter users connected or did not connect to transit (N = 48,301).

City	Connected to transit N = 11,510 (23.8 % of the total sample)	Did not connect to transit N = 36,791 (76.2 % of the total sample)
Ann Arbor, MI	480 (4.17 %)	2,247 (6.11 %)
Atlanta, GA	441 (3.83 %)	1,554 (4.22 %)
Baltimore, MD	1,094 (9.50 %)	3,215 (8.74 %)
Charlotte, NC	392 (3.41 %)	1,239 (3.37 %)
Detroit, MI	362 (3.15 %)	946 (2.57 %)
Fort Collins, CO	342 (2.97 %)	1,288 (3.50 %)
Gainesville, FL	131 (1.14 %)	551 (1.50 %)
Grand Rapids, MI	842 (7.32 %)	3,284 (8.93 %)
Lansing, MI	706 (6.13 %)	1,632 (4.44 %)
Los Angeles, CA	574 (4.99 %)	1,016 (2.76 %)
Orlando, FL	464 (4.03 %)	2,006 (5.45 %)
Providence, RI	511 (4.44 %)	1,900 (5.16 %)
Sacramento, CA	715 (6.21 %)	2,385 (6.48 %)
Salt Lake City, UT	855 (7.43 %)	2,517 (6.84 %)
San Diego, CA	700 (6.08 %)	2,194 (5.96 %)
San Francisco, CA	1,119 (9.72 %)	3,119 (8.48 %)
Santa Monica, CA	502 (4.36 %)	1,692 (4.60 %)
Seattle, WA	530 (4.6 %)	1,767 (4.80 %)
Stillwater, OK	191 (1.66 %)	682 (1.86 %)
Tampa, FL	559 (4.86 %)	1,557 (4.23 %)
Total	11,510 (100 %)	36,791 (100 %)

Note: Percentages reported in parentheses for each city are "column percentages" (i.e. percentage of observations from that column that are from that service area)

a substantial error of at most 66.7%. Moreover, the uncertainty introduced by the offset may increase the variability in estimates, leading to larger standard errors and less precise inference. There are 1450 trips between 100 m and 300 m, comprising 3.00 % of the filtered sample. While measurement error can pose a significant challenge for small datasets, the substantial sample size in our study likely minimizes the impact of any bias resulting from the issue.

Table 1 lists the cities where the survey was deployed. Out of the 48,301 trips analyzed, there are 23.8 % cases in which users reported that they had connected to transit before or after their e-scooter trip.

3.3. Modeling Approach

In this study, to investigate what may drive e-scooter users' decisions to connect with transit, we use a binary logit model considering the decision of whether the user connected to transit as the dependent variable. Binary logit models have been widely used as the modelling approach to estimate the effects of exogenous factors on individuals' binary choices (e.g., connecting to transit or not, after or before an e-scooter trip) (Afghari et al., 2020). These models are fundamentally based on the random utility theory, which postulates that individuals choose between alternatives based on observed and unobserved factors. A utility function is defined for the individual's choice behavior, which consists of a deterministic component and an error term (McFadden, 1973). For any e-scooter user, the utility of connecting to transit before or after the trip is given by the sum of a deterministic component of the utility, which can be written as a linear equation of the explanatory variables and a random term capturing the impacts of the unobserved factors.

The following variables were used in our analysis:

Table 2
Survey responses based on whether e-scooter users connected to transit or not (N = 48,301).

	Connected to transit (N = 11,510 (23.8 %))		**Did not connect to transit** (N = 36,791 (76.2 %))	
When did you decide to take the e-scooter for this trip?				
Spur of the moment	7,236	(62.9 %)	19,644	(53.4 %)
Planned shortly before starting the trip	2,541	(22.1 %)	11,333	(30.8 %)
Planned earlier in the day or days before	1,733	(15.0 %)	5,814	(15.8 %)
Total	11,510	(100 %)	36,791	(100 %)
What factors influenced you to choose an e-scooter for this trip? *				
Fastest option	5,654	(49.1 %)	22,815	(62.0 %)
Easiest, most convenient option	2,552	(22.2 %)	13,847	(37.6 %)
It's fun	2,114	(18.4 %)	9,854	(26.8 %)
I do not own a car	2,096	(18.2 %)	4,665	(12.7 %)
Public transit is too far/too slow	1,668	(14.5 %)	3,774	(10.3 %)
Least expensive option	1,219	(10.6 %)	4,650	(12.6 %)
Best option due to COVID-19	1,062	(9.2 %)	1,639	(4.5 %)
Less polluting/more environmentally friendly	1,038	(9.0 %)	3,789	(10.3 %)
Safer than alternative options	757	(6.6 %)	1,779	(4.8 %)
If not by e-scooter, how would you have taken the trip that just ended?				
Less than 1 mile	**5,751**	**(50.0 %)**	**19,069**	**(51.8 %)**
Private car	1,022	(17.8 %)	1,970	(10.3 %)
Rideshare	474	(8.2 %)	1,274	(6.7 %)
Walk	2,686	(46.7 %)	13,969	(73.3 %)
Transit	689	(12.0 %)	466	(2.4 %)
Personal bike	315	(5.5 %)	388	(2.0 %)
Bikeshare	31	(0.5 %)	32	(0.2 %)
Other	290	(5.1 %)	462	(2.4 %)
Nothing (skip trip)	244	(4.2 %)	508	(2.7 %)
Between 1—2.5 miles	**3,883**	**(33.7 %)**	**12,594**	**(34.2 %)**
Private car	754	(19.4 %)	2,087	(16.6 %)
Rideshare	459	(11.8 %)	1,891	(15.0 %)
Walk	1,407	(36.3 %)	6,393	(50.8 %)
Transit	622	(16.0 %)	809	(6.4 %)
Personal bike	203	(5.2 %)	381	(3.0 %)
Bikeshare	22	(0.6 %)	15	(0.1 %)
Other	214	(5.5 %)	433	(3.5 %)
Nothing (skip trip)	202	(5.2 %)	585	(4.6 %)
More than 2.5 miles	**1,876**	**(16.3 %)**	**5,128**	**(13.9 %)**
Private car	420	(22.4 %)	1,083	(21.1 %)
Rideshare	178	(9.5 %)	644	(12.6 %)
Walk	656	(35.0 %)	2,143	(41.8 %)
Transit	274	(14.6 %)	288	(5.6 %)
Personal bike	105	(5.6 %)	170	(3.3 %)
Bikeshare	1	(0.1 %)	2	(0.0 %)
Other	110	(5.9 %)	228	(4.5 %)
Nothing (skip trip)	132	(7.0 %)	570	(11.1 %)

Note: * The question allowed multiple choice options with a 'select all that apply' format. Therefore, percentages may not add up to 100.

i. *Time of day variables*: We define four dummy variables to capture the time of day when the users made their e-scooter trip. The *AM peak* is defined as all hours between 7 am and 10 am, *midday* captures all times between 10 am and 3 pm, the *PM peak* contains all times between 3 pm and 7 pm, and *night* contains all times between 7 pm and 6 am.
ii. *Factors motivating the use of e-scooters for the trip*: respondents were asked to select the factors that motivated them to choose an e-scooter as the mode of travel for their trip.
   Table 2 provides the verbatim text of the nine options that were presented to respondents in the questionnaire.

iii. *When the respondent decided the take the trip*: The three categories listed in the questionnaire included the "spur of the moment", planned shortly before starting the trip, and planned earlier in the day or days before.
iv. *Travel time*: The duration of the trip from start to end is also available in the dataset.

The dataset supplied by the e-scooter company was augmented with information obtained from various urban and built environment datasets to enable controlling for these characteristics in the analysis. We construct a Euclidean line between the (deflected) start and end points of each e-scooter trip and capture the average urban and built environment characteristics listed below. We consider 125-meter buffers around each e-scooter trip line. The following variables were obtained:

v. *Population density*: Data on population density is obtained from the Smart Location Database (SLD). A weighted average of the total population is calculated and then divided by the area of each buffer to obtain population density for each buffer.
vi. *Employment density*: This variable is extracted from SLD and is calculated as a weighted average for the census block groups that fall within the buffer. It captures the potential attractiveness of an area in terms of commute trips.
vii. *POI count*: Data on points of interest (POIs) is sourced from Open Street Maps (OSM). We selected points of interest in each buffer that are open to the public, such as banks, stores, hairdressers, etc., that are likely to attract certain types of trips.
viii. *Transit index*: Sourced from SLD by census block group, the transit index ranges from 0 to 1, with higher values indicating better access to transit.
ix. *National walk index*: sourced from SLD, the National Walk Index ranges from 1 to 20, with higher values indicating better pedestrian access.

The SLD is a publicly available data product and service provided by the US EPA Smart Growth Program. The SLD reports or derives variables from the US Census American Community Survey (ACS). This data source maintains data from the 1-year or 5-year ACS database. We have used the 2018 5-year estimates in this study.

4. Results and discussion

Table 2 presents the distribution of user responses to the survey questions, segmented by whether users connected to transit or not.

4.1. When the e-scooter trip was planned

More than half of riders reported deciding to use an e-scooter at the spur of the moment. Also, a larger proportion of those who connected to transit reported a spontaneous decision (62.9 %) than their counterparts who did not connect to transit (53.4 %). Those who connected to transit were less likely to report planning to use an e-scooter shortly before starting their trip (22.1 %), compared to users who did connect to transit (30.8 %). The share of riders who reported planning their e-scooter use a day or more in advance was similar for those who connected to transit (15.0 %) and those who did not (15.8 %). These results suggest that a substantial portion of those users who connected to transit likely made last-minute decisions to use e-scooters, possibly after spotting one on the street or upon exiting a public transit station or stop.

4.2. Motivations for using an e-scooter

Respondents were asked about which factors motivated them to choose an e-scooter for their trip. The top three influencing factors were the same for both groups of respondents: riding shared e-scooters is *the fastest option*, *the easiest and most convenient option*, and *it's fun*. We find that those who connected to transit were more likely to report that other factors were also important, such as car availability (and lack thereof), concerns to COVID-19 (as the data were collected in 2021, this was still an important factor affecting travel choices), and public transit being far away or slow. For example, about 18.2 % of users who connected to transit and 12.7 % of users who did not connect to transit said that one of the influencing factors was that they do not own a car. This highlights how shared e-scooters can offer mobility options to those who do not own a car and potentially create a space to make more users comfortable not owning a car.

4.3. Modes displaced by e-scooter use

Table 2 also summarizes the responses to the mode displacement question, segmented by connection to transit and by the e-scooter trip distance into three distance categories: less than 1 mile, between 1—2.5 miles, and more than 2.5 miles.

About half of the trips in the sample are less than 1 mile in length, both among riders who connected with transit (50.0 %) and those who did not (51.8 %). Roughly one-third were between 1 and 2.5 miles, among riders who connected with transit (33.7 %) and those who did not (34.2 %). A slightly larger share of trips was longer than 2.5 miles among riders who connected with transit (16.3 %) than those who did not (13.9 %).

As shown in Fig. 2, and not surprisingly, displacement of automobile trips, including private car and rideshare, is more common as trips get longer. This is consistent with the literature and confirms concerns about VMT calculations for trip displacements in previous studies that do not

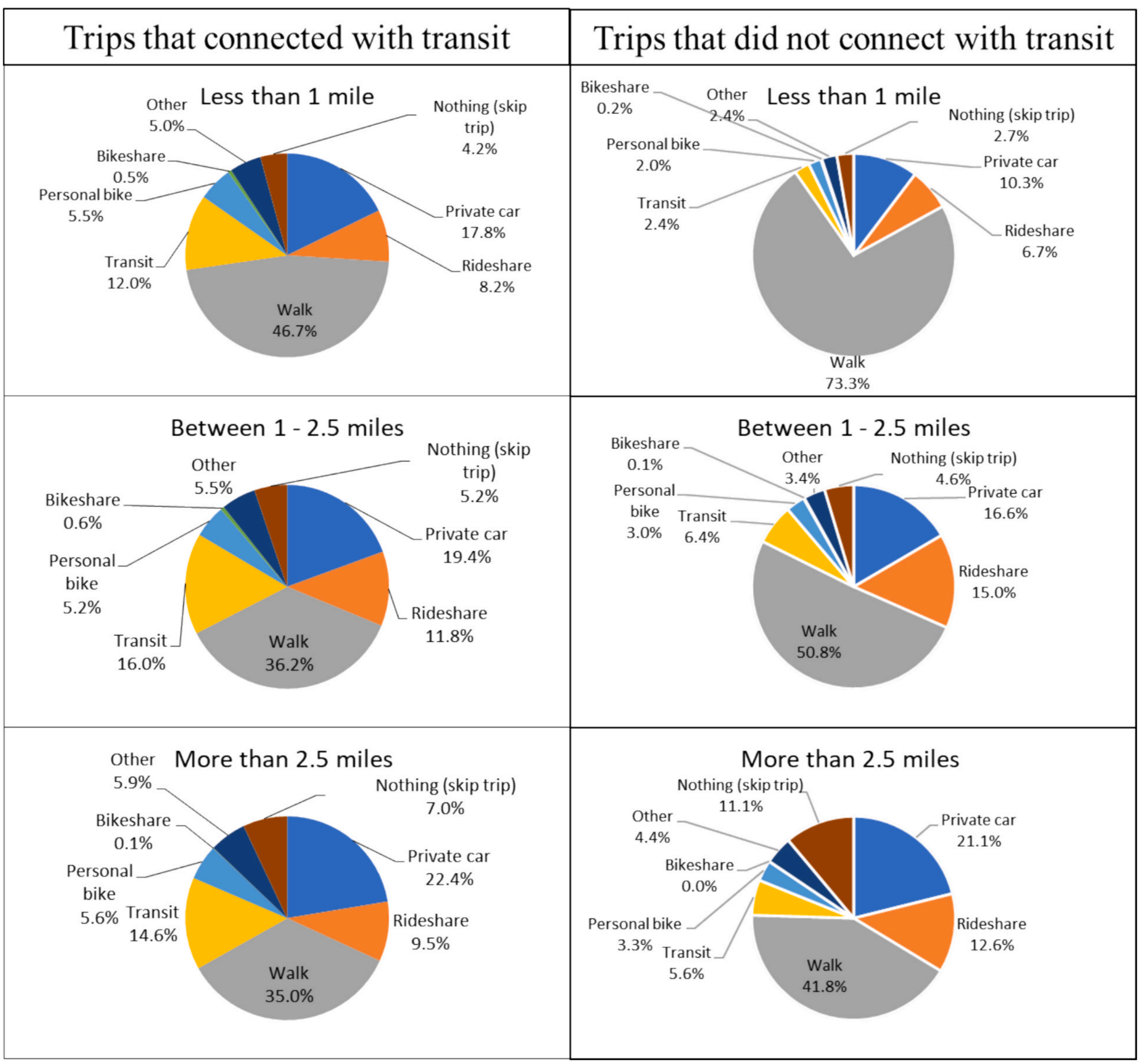

Fig. 2. Self-reported modal substitution segmented by whether the e-scooter users connected to transit or did not connect to transit and by trip distance (N = 48,301).

account for mode displacement by distance. For example, Meroux, Broaddus and Chan (2022) found that the share of car mode displaced is underrepresented when using the share of trips metric and not accounting for distance, while walk mode is consistently overrepresented. For the longest trips, those over 2.5 miles, we see that roughly the same proportion of e-scooter trips replace automobile trips (private car and rideshare) among riders who connected with transit (33 %) as those who did not (34 %). Interestingly, a higher proportion of trips displaced ridesharing for e-scooter trips that are between 1 and 2.5 miles as compared to those that are longer than 2.5 miles.

Walking is the most frequent mode that is displaced by the use of e-scooters, with the largest proportion of e-scooter trips replacing walking for trips under 1 mile. Fewer walk trips were displaced among riders connecting to transit than those who did not. While 46.7 % of riders who connected to transit reported they substituted an e-scooter for walking, 73.3 % of riders who did not connect to transit would otherwise have walked. This relates to the fact that e-scooters most often replace walking for short-distance trips. Interestingly, 12.0 % of riders who connected to transit reported that they took a transit trip, compared to 2.4 % of riders who did not. In this case, we speculate that some users are using an e-scooter rather than a connecting transit service to reach a larger hub, for example, to avoid waiting for the transit vehicle on a secondary route with lower quality of service.

Mode displacement patterns were similar for trips between 1 and 2.5 miles in length and those longer than 2.5 miles, but with larger proportions of motorized modes displaced for longer trips, as discussed above. The mode displacement for transit offers some interesting insights: 12.0 % to 16.0 % (depending on distance) of those connecting to transit said they would have used transit if the e-scooter were not available. This may be interpreted in several ways – perhaps these respondents would have used other forms of public transit (e.g., taken a bus to access rail); or perhaps the user interpreted the question to report that they would have taken their entire trip by transit, instead of using the e-scooter to connect to transit. This seems to imply that e-scooters may be shortening first/last mile connection times by offering a more convenient alternative option for transit users who would otherwise walk to/from transit stops. For such e-scooter users, we may infer that the entire trip may have been quicker with the e-scooter than without.

Table 3
Cross-tabulation between transit displacement and connection to transit (N = 48,301).

			Connection to Transit No	Yes	Total
Transit Displaced	**No**	Count	35,228 (A)	9,925 (B)	45,153
		% within Transit displaced	*78.0 %*	*22.0 %*	*100.0 %*
		% within Connection to transit	*95.8 %*	*86.2 %*	*93.5 %*
		% of Total	72.9 %	20.5 %	93.5 %
	Yes	Count	1,563 (C)	1,585 (D)	3,148
		% within Transit displaced	*49.7 %*	*50.3 %*	*100.0 %*
		% within Connection to transit	*4.2 %*	*13.8 %*	*6.5 %*
		% of Total	3.2 %	3.3 %	6.5 %
Total		Count	36,791	11,510	48,301
		% within Transit displaced	*76.2 %*	*23.8 %*	*100.0 %*
		% within Connection to transit	*100.0 %*	*100.0 %*	*100.0 %*
		% of Total	76.2 %	23.8 %	100.0 %

4.4. Segmentation of e-scooter riders

Table 3 provides a further exploration of the modal integration between shared e-scooters and public transportation. The sample is split into four groups based on exogenous segmentation using the two variables *connection to transit* and *transit displaced.* These are both binary variables. The former is defined using the survey question '*did you connect with public transit before or after your Spin trip?*'. Respondents who answered 'yes' to this question were assigned a value of 1 for the *connection to transit* variable, 0 otherwise. The *transit displaced* variable is defined based on the survey question *'if not by e-scooter, how would you have taken the trip that just ended?'*. Respondents who answered 'transit' to this question were assigned a value of 1 for the *transit displaced* variable, 0 otherwise. Based on this segmentation, the sample can be categorized into the following four groups:

i. *No interaction*: E-scooter users who did not displace transit and did not connect to transit (quadrant A of Table 3). These users may be interpreted as having no interaction with public transit at all during their e-scooter trip. This group makes up the vast majority (72.9 %) of the trips in the sample.
ii. *Complements*: E-scooter users who stated that they did not displace transit for the e-scooter and did connect to transit (quadrant B). Such trips may be interpreted as cases where e-scooters clearly complement transit use. Perhaps they would have walked to transit instead, and e-scooters may have provided a faster alternative to walking. This category constitutes the second largest subgroup in the sample (20.5 % of the sample).
iii. *Substitutes*: E−scooter users who said they displaced transit and did not connect to transit, shown in quadrant C. This category of trips may be interpreted as clearly having substituted public transportation with the traveler who used the shared e-scooter instead of transit to make their trip (3.2 % of the sample).
iv. *Mixed effects*: E-scooter users who said they displaced transit and also connected to transit (quadrant D). Such users may be interpreted as having used shared e-scooters to access public transit as part of a multimodal (or better say, intermodal) trip. For such trips, we may interpret that e-scooters provided access and hence made life easier for users. It may also imply that for part of the trip, transit was displaced, but not for the entire trip, since the respondents claim they did connect to public transportation at some point. For example, someone might have intended to walk or use a bus to access a train station, but then decided to use a shared e-scooter instead when they saw one in the street. We also speculate that some respondents may have answered 'yes' to the survey question if they had used transit at some point during the same day prior to their e-scooter trip, but perhaps not as a leg of the same trip, so this ambiguity needs to be considered among the potential limitations affecting the study. Such respondents constitute 3.3 % of the trips in the sample.

In total, approximately 6.5 % of the respondents (i.e., those in quadrants C and D) said that they would have used public transportation instead of the shared e-scooter for their trip. As the information in Table 3 shows, considering this information alone, at face value, may be misleading. Half of these respondents said that while they would have used transit if the e-scooter had not been available, they still chose to connect to transit during their trip. This suggests that the extent of transit displacement cannot be accurately assessed solely based on respondents' stated alternative mode choices in the absence of e-scooters, as done in prior studies. Such approaches may overestimate the degree to which e-scooters substitute for transit. In reality, some individuals who report choosing transit as their alternative may still be using transit for part of the trip, with the e-scooter replacing only a segment rather than the entire journey. Our findings about complementarity (about one in every five e-scooter trips) align to some extent with Luo et al. (2021), who found that 29 % of shared e-scooter trips in Indianapolis complement public transport. However, they also find a potentially competing relationship for 27 % of trips, which is much higher than our results show. We find that most e-scooter trips (72.9 %) had no interaction with transit. However, it is possible that this proportion is inflated due to the fact that our survey was conducted during the pandemic.

4.5. Relationship between transit connection and trip distance

Fig. 3 shows the distribution of trip distances in the sample. The distribution is positively skewed with a mean value of 1.440, a median value of 0.974 and a standard deviation of 1.449. Our sample's average trip length aligns with findings from previous research, which shows that e-scooter trips were generally quite short. Most studies found trip lengths averaging between 1 and 1.5 miles (NABSA, 2020; NACTO, 2023). According to the latest NABSA report, the average shared e-scooter trip is 1.2 miles long, slightly shorter than the average shared e-bike trip (2.0 miles) and the average shared pedal bike trip (1.4 miles). In our sample, most trips (51.39 %) fall at relatively short distances of one mile or less. The distribution has a long right tail implying that although the bulk of trips are short, there are some notably longer trips that extend the tail farther to the right. Overall, the data is clustered over short distances with a smaller proportion of much longer trips pulling the mean upward.

Table 4 shows the average distance of e-scooter trips made by each rider segment identified above, along with results of a *t*-test of statistical significance against the overall sample average. E-scooter users who substituted a transit trip with a shared e-scooter on average travelled a statistically significant longer distance by e-scooter than the rest of the sample. The average distance of the e-scooter trips that replaced the transit trips was 1.77 miles, significantly higher than the full sample average. This is expected as this trip consists of the first/last distance the respondents would cover to access transit as well as the distance individuals would travel by transit. We speculate that riders substituting e-scooters for longer trips that they would otherwise make by transit may do so for the motivating factors reported above, i.e., that the e-scooters provide a faster alternative to transit and are more affordable than rideshare, a convenient solution especially for those who do not have a car available. An interesting avenue worth exploring in future research is whether e-scooters expand the transit shed by offering a fast and convenient first- and last-mile connection.

The average length of the e-scooter trips clearly complementing transit was 1.51 miles. These 'regular distance' trips connecting to transit imply that e-scooters were used as a first/last mile connection to transit. Notably, this distance (~1.5 miles) is longer than distances typically used to estimate the 'walking shed' for transit, which is usually considered to be in the order of 0.25 to 0.5 miles. This implies that e-scooter users are able to access fixed route public transit from further flung locations, possibly expanding the transit access shed.

4.6. Binary logit model estimation results

Table 5 shows the results of the estimation of the binary logit model. The dependent variable is *connection to transit* which is based on the rider's response to the question '*did you connect with public transit before or after your Spin trip?*'. The column at the far right contains values for the exponential value of the coefficients, which helps form interpretations in terms of relative probabilities.

The explanatory variables are categorized into three broad groups: trip level attributes, reasons for using the e-scooter, and neighborhood characteristics. All coefficients are interpreted as the impact of that variable on the probability of an e-scooter trip being used for connecting to transit, given that the respondent decided to take an e-scooter for that trip. *Travel time* is found to be significant and positive, implying that trips of longer duration have a higher probability of connecting to transit. The *trip planning* variable is categorical and is based on the question *'when did you decide to take the e-scooter for this trip?'*. This variable is assigned a value of 1 if the rider answered, 'spur of the moment', a value of 2 if the rider responded with 'planned shortly before starting the trip' and a value of 3 if the response was 'planned earlier in the day or days before'. Considering the first category as the base, the results show that compared to e-scooter trips that were taken on the spur of the moment, trips that were planned beforehand have a lower probability of connecting to transit, all else equal. This suggests that users who connect to transit do so spontaneously, e.g. when they see a scooter available near the transit stop. It may also imply that the dockless nature of these services does not allow people to plan much in advance. In terms of the time of day when the trip was made, users who started the e-scooter trip during the PM peak and night are more likely to connect with transit as compared to those who took the trip in AM peak or midday. This may imply that e-scooter users traveling during PM peak or at night may be using the e-scooter as a faster way to reach the transit station which may invoke a sense of safety.

The coefficients of the variables in the *reasons for using an e-scooter* category imply that those who said they used an e-scooter for their trip because it is fast, easy or convenient, and fun had a lower probability of connecting to transit on their e-scooter trip, all else equal. The coefficients for some motivation factors were positive and significant, including for e-scooter riders who do not own a car, say that transit is too far or slow, e-scooters are the best option due to COVID-19, and it is a safe option – meaning that these respondents made trips that were more likely to connect to transit, all else equal. All the variables in the *reasons for using an e-scooter* category are found to be highly significant. Respondents in the sample who find that transit is too far or too slow have a

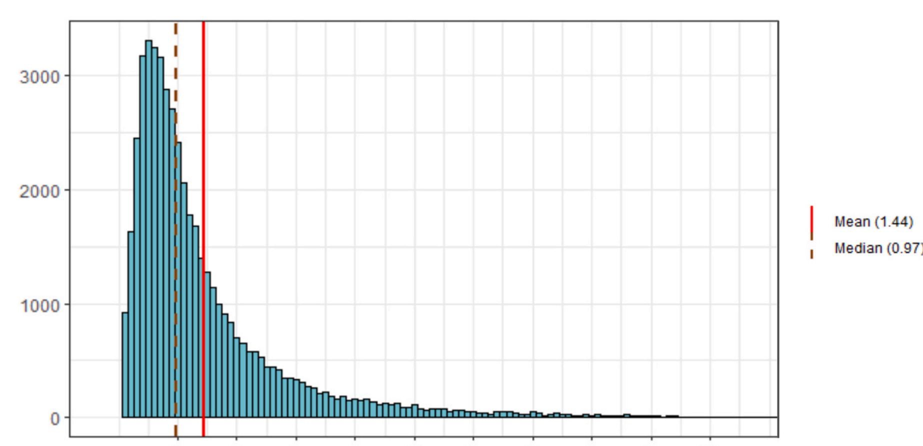

Fig. 3. Distribution of trip distances in miles (N = 48,301).

Table 4
Summary statistics of selected categories (N = 48,301).

Transit displaced	Connection to transit	Interpretation	Observations	Average distance (miles)	*t*-test	p-value
No	No	No interaction	35,228 (72.93 %)	1.40	−5.48***	<0.001
No	Yes	Complements	9,925 (20.55 %)	1.51	4.28***	<0.001
Yes	No	Substitutes	1,563 (3.24 %)	1.77	9.34***	<0.001
Yes	Yes	Mixed effects	1,585 (3.28 %)	1.59	4.01***	<0.001
Full sample			48,301	1.44		

Notes: (.) significant at 10% level, * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level. Observation proportions of totals provided.

Table 5
Model estimation results of binary logit model for the e-scooter connection to transit (N = 48,301).

	Estimate β_K	Standard error	t-ratio	p-value	e^{β_K}
Alternative Specific Constant (ASC)	−0.269	0.117	−2.290	0.022*	0.764
Trip attributes					
Travel time (minutes)	0.002	0.001	1.991	0.047*	1.002
Trip planning (L2)	−0.373	0.027	−13.624	< 0.001***	0.689
Trip planning (L3)	−0.157	0.032	−4.831	< 0.001***	0.855
PM peak	0.087	0.029	2.965	0.003**	1.091
Night	0.224	0.028	8.093	< 0.001***	1.251
Reasons for using the e-scooter					
Fastest option	−0.465	0.023	−19.892	< 0.001***	0.628
Easiest, most convenient option	−0.668	0.028	−23.644	< 0.001***	0.513
Least expensive option	−0.055	0.040	−1.378	0.168	0.946
Don’t own a car	0.465	0.032	14.353	< 0.001***	1.592
Public transit is too far/ too slow	0.608	0.037	16.343	< 0.001***	1.837
Best option due to COVID-19	0.681	0.046	14.701	< 0.001***	1.976
It’s fun	−0.703	0.025	−28.465	< 0.001***	0.495
Safer than alternatives	0.205	0.050	4.076	< 0.001***	1.228
Less polluting	−0.056	0.043	−1.305	0.192	0.946
Neighborhood characteristics					
Population Density	−16.526	4.265	−3.875	< 0.001***	< 0.001
Employment density	1.736	0.660	2.632	0.008**	5.675
National walk index	−0.009	0.006	−1.619	0.105	0.991
Travel time (minutes) x Population density	0.372	0.140	2.647	0.008**	1.450
LL(0)					−33,479.7
LL(C)					−26,522.53
LL(final)					−24,628.06
$\rho^2_{EL-BASE}$					0.2644
Adjusted $\rho^2_{EL-BASE}$					0.2632
$\rho^2_{MS-BASE}$					0.0714
Adjusted $\rho^2_{MS-BASE}$					0.0700
AIC					49,332

Notes: (.) significant at 10% level, * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level. 20 regional controls were included in this model, with San Francisco used as reference. All regional control coefficients are negative and significant (p-values between 0.1% and 5%) except for Detroit and Los Angeles, whose coefficients are not statistically significant.

higher probability of connecting to transit – this may imply that areas where the transit network is weak and shared micromobility is available may see a higher number of transit and e-scooter connections. The policy implication here is that a weak transit network may be better utilized if that area has shared micromobility options. Not owning a car also positively affects the probability that an e-scooter rider would connect to transit. This implies that respondents with limited mobility options use e-scooters and transit as complimentary modes. The policy takeaway from this finding is that local governments can support people with limited mobility options by integrating e-scooters and transit networks.

Some of the *neighborhood characteristics* have a significant impact on the decision to connect to transit. Population density in the surroundings of where the e-scooter trip was made has a negative impact on the probability of the e-scooter trip connecting to transit. This may be explained by the expectation that low density areas are usually served by transit stops that are far away from each other, so in these areas there is a higher likelihood that e-scooter trips can help access/egress transit stops thus connecting to transit. Empirical studies yield mixed outcomes on how population density affects the integration of e-scooters with public transit. For example, our findings align with Yan et al. (2021) who note that complementarity was mostly noted outside downtown Washington DC, whereas the two modes compete in the downtown area. However, other studies discovered a significant relationship between e-scooter and transit trips in downtown areas (Zuniga-Garcia at al., 2022). The coefficient for employment density is positive and significant. This seems to imply that areas with high employability experience more e-scooter and transit connections. The data set used for this study does not contain more information on this phenomenon, but future studies can use this as a reference to explore if some individuals are using e-scooters to connect to transit for commute trips. Guo and He (2020) find that residential and industrial areas, in particular, exhibit a higher level of integrated use, driven largely by commute trips (Javadiansr et al., 2024). While the impact of this variable may need further exploration to be understood fully, especially when combining this finding with that of population density, it may be the case that since e-scooters have become the norm in many cities, people may be comfortable adopting them also to commute from lower-density areas with lower walk accessibility to transit to jobs located in the downtown that are along major transit corridors. We also include in our analysis an interaction term between travel time and population density. A statistically significant interaction term is consequential because of a nonlinear multiplicative effect. This interaction term has a positive coefficient implying that higher population density amplifies the effect of trip time on e-scooter trips connecting to transit. This could suggest that places with higher population density have a stronger impact of longer e-scooter trips connecting to transit. The policy implication of this finding is that local governments can subsidize longer trips over shorter ones, especially in dense cities. It may also imply that having e-scooter stations further spread out from the city center may encourage transit use. The inclusion of an interaction term can potentially lead to multicollinearity. We therefore use the variance-inflation factor (VIF) test to rule out multicollinearity. The results of the test are reported in Table A1 of the Appendix. The generalized VIF, or GVIF, goes beyond the traditional VIF as it applies to multiple degrees of freedom. Table A1 in the Appendix reports the GVIF along with the value of GVIF^1/(2*df), which provides a per degree-of-freedom inflation that allows for a fair comparison across variables with varying df (Fox and Monette, 1992). Considering a threshold of 2 for the GVIFˆ1/(2*df) value, we find that including the interaction term does not inflate the standard errors to an extent that merits remedial action.

The POI count and transit score do not have a significant impact on the dependent variable. We retain the national walk index variable in the model as it increases the overall goodness of fit of the model, which may be due to correlations amongst the variables as well as some contribution of this variable to explaining choices, even if the coefficient is not found to be statistically significant at the 5 % level due to larger noise in the data (which leads to larger standard errors). However, the POI count and transit index did not enhance the model fit and were therefore excluded from the analysis to maintain parsimony. For regional controls, we set San Francisco as the reference. All city dummy coefficients are significantly lower than the base, except for Detroit, Lansing and Los Angeles. The former two cities have insignificant coefficients, and Los Angeles has a positive and significant coefficient. This implies that the average impacts of unobserved factors in most cities point to e-scooter users being less likely to connect to transit than those in San Francisco, Detroit, Lansing and Los Angeles.

5. Conclusions

This study explores the interactions between the use of shared e-scooters and public transit by investigating the factors that drive shared e-scooter users' decisions about whether or not to connect to transit services before or after their e-scooter trip. Using a novel dataset with linked trip and survey data, we explore the factors that influence riders' use of e-scooters as a substitute for and complement to public transit with a large sample of almost 50,000 e-scooter trips from 20 US cities.

Among other major findings of the study, our analysis reveals that what may first appear to be a substitution of transit trips with shared e-scooters may not always be true. Approximately 6.5 % of the respondents in the sample said that they would have used public transportation for their trip instead of the e-scooter. However, about half of the respondents who said they would have used transit if the e-scooter were not available also reported that they did actually connect to transit either before or after that e-scooter trip. In other terms, what may initially appear as pure substitution with transit can be better described as a mix of substitution and complementarity between the two modes. Previous studies that solely relied on the self-reported mode choice in case the e-scooter was not available likely overestimated the mode substitution of e-scooters with transit. Thanks to the availability of detailed information of the e-scooter trip distances (and locations where the trips are made), we find that the average length of the e-scooter trips complementing transit was 1.48 miles, implying that e-scooters are used as a first/last mile connection to transit over distances that would be unpleasant to walk.

In the study, we further investigate the factors that explain why e-scooter users connect to transit by estimating a binary logit model of the decision of e-scooter users to connect (or not) to transit for their trip. The results show that individuals' motivation factors to use an e-scooter play a significant role in explaining whether or not they are connected to transit. Those motivated by not owning a car, considering transit too far or slow, and considering e-scooters a safe option were more likely to connect to transit, all else equal. Individuals who made a spontaneous decision to take the e-scooter for their trip are more likely to connect to transit compared to those who plan more in advance to use an e-scooter. Moreover, trips made in the night and PM peak hours are more likely to connect to transit than trips made during the midday and AM peak. Travel duration is also found to positively impact the probability that an e-scooter trip connects to transit.

The findings from this study have multiple policy implications for two stakeholders: micromobility providers and transit agencies. The finding that spontaneous e-scooter users are more likely to connect to public transit than those who plan their e-scooter trips has important implications for transportation planning. It suggests that e-scooters function as a flexible, on-demand solution for first- and last-mile connectivity rather than as a standalone mode for planned trips. Transit agencies and micromobility providers can capitalize on this user behavior by improving the visibility and availability of e-scooters near transit hubs, enhancing real-time information systems, and removing barriers to spontaneous access (e.g., through seamless app integration). Micromobility providers should consider rebalancing vehicle fleets to ensure higher availability of e-scooters near transit hubs during PM peak and nighttime hours. These initiatives could ultimately increase multimodal travel and public transit use. Some public transit agencies are already collaborating with micromobility providers, including micromobility as an important component in their plan for first and last mile connection to public transit (Mohiuddin, 2021).

While this study provides several pieces of novel information that contribute to expanding the knowledge in the literature about the adoption of e-scooters and their relationship with public transit use, it is also constrained by certain limitations that are worth mentioning. First, the dataset for the study does not include exact GPS locations of the trips nor the route taken by the e-scooter users. This limitation, though, is expected to have a relatively limited impact on the analyses presented in this study. The data also does not provide information about which trips are being made by the same individual, so frequent users might be represented with multiple trips in the same dataset. Second, the research team does not have access to the users' socio-demographic data. This may cause potential biases and over-evaluation of the impacts of urban and built environment variables used in the model, due to a form of omitted variable bias, as these variables might pick up some of the impacts of the socio-demographic variables. Third, there are certain limitations due to how the survey question that is used as a dependent variable in the model was asked in the survey ("*Did you connect with public transit before or after your Spin trip?*"). We do not know whether users connected with transit immediately before or after their e-scooter trip, or whether the transit connections were part of a longer multimodal/inter-modal trip. Further, some users might have interpreted this question as simply reporting whether they used public transit at some other point before/after the e-scooter trip during the same day. This limitation might cause an overestimation of the number of trips that are connected to transit. Fourth, the 100-meter offset to anonymize the data may be considered rather large in an urban setting. Anonymization methods introduce random noise in the data so that each location is perturbed in an unpredictable direction, producing measurement error. For trips shorter than 300 m, this deflection can produce a substantial error of at least 33.3 %. However, trips less than 300 m only comprise 3.00 % of the total sample. Therefore, we expect this bias should not be substantial given the large size of our dataset. Fifth, the sample used for this study was collected during the pandemic, a time during which commute and travel patterns had completely shifted from the norm. Even though there was no strict lockdown in US cities, many people were avoiding crowds and being outdoors. Our results show that most e-scooter trips (72.9 %) had no interaction with public transit. We suspect that this value was higher than it would be in the absence of the pandemic. Finally, we could only use data from users who consented to take the survey and authorized the use of their data for research purposes, which might lead to self-selection issues (including eventual respondent biases) and limit the representativeness of the sample.

Future directions for research on the interactions between e-scooters and transit may involve a deeper exploration of the categories identified in the descriptive analysis, that is, whether there was no interaction between transit and e-scooters, whether they were found to be complements, substitutes or some combination of both, in particular to address the limitations of the present study and increase the accuracy and reliability of the results. We also plan to investigate whether e-scooters play a significant role in expanding the catchment areas of transit stations. Future extensions in this field may yield important post-pandemic insights since using the e-scooter due to COVID-19 was a temporary issue. Other important dimensions that we plan to explore include investigating how sociodemographic characteristics and attitudinal variables may impact travel behavior and the integration between e-scooters and public transit. Future extensions of our work may involve trying to match trip data with rider data, including sociodemographic and attitudinal data. This may allow us to use more sophisticated modeling approaches such as integrated choice and latent variable models.

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CRediT authorship contribution statement

Maha Ahmad: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hossain Mohiuddin:** Investigation, Formal analysis, Data curation, Writing – review & editing. **Kailai Wang:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Andrea Broaddus:** Writing – original draft, Writing – review & editing, Conceptualization, Visualization, Methodology, Investigation, Funding acquisition. **Mike Fortier:** Project administration, Investigation, Funding acquisition. **Giovanni Circella:** Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

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

Table A1 shows the results of the VIF test for multicollinearity.

Table A1
Results of VIF test.

	GVIF	Df	GVIF^(1/(2*Df))
Travel time (minutes)	2.098	1	1.449
Fastest option	1.100	1	1.049
Easiest, most convenient option	1.216	1	1.103
Least expensive option	1.224	1	1.106
Don’t own a car	1.134	1	1.065
Public transit is too far/too slow	1.229	1	1.109
Best option due to COVID-19	1.150	1	1.072
It’s fun	1.112	1	1.054
Safer than alternatives	1.140	1	1.068
Less polluting	1.215	1	1.102
Trip planning	1.071	2	1.017
Population density	2.558	1	1.599
Employment density	1.317	1	1.148
PM peak	1.418	1	1.191
Night	1.509	1	1.228
National walk index	3.053	1	1.747
Travel time (minutes) x Population density	2.720	1	1.649

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