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Measuring the impacts of dockless micro-mobility services on public transit accessibility

Luyu Liu [a,b,*], Harvey J. Miller [a,b]

[a] Department of Geography, The Ohio State University, USA
[b] Center for Urban and Regional Analysis (CURA), The Ohio State University, USA

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ABSTRACT

Dockless micromobility services have potential as a fast and flexible solution to short-distance trips and public transit's first-mile/last-mile (FM/LM) access problem; however, these services also have limitations, including uneven spatial distribution, low capacity, and user out of pocket expense. This can impact on the ability of micromobility to enhance public transit accessibility. We introduce *accessibility increment* measures – the amount by which public transit accessibility improves due to micromobility services. We apply these measures to hypothetical trips using public transit and micromobility data from Columbus, Ohio, USA. We find dockless scooters can increase accessibility by multimodal public transit trips, with increments in the first mile significantly outweighing last mile accessibility increments. Accessibility increments are highly concentrated in the city center due to the distributions of scooters and bus stops. We also find that scooters' accessibility increment contribution is highly unequal: a small number of scooters contribute most of the accessibility increments. Monetary cost simulations show that the first-mile accessibility increment will rapidly decrease and last-mile increment slightly increase with lower willingness to pay. Capacity simulations show a group of users' accessibility increment will rapidly decrease as the group size increases, but this depends on whether they are competing or collaborating for scooters. Our results show that despite showing promising potentials, vendors and policymakers still need to address these issues to make collaboration between public transit and dockless micromobility sustainable and equitable. The paper provides measures and evidence for future transit and micromobility planning for scooter vendors and transit authorities.

1. Introduction

Dockless micro-mobility services have potential as an emerging transportation mode. In 2019 alone, the US experienced 96 million trips on dockless scooters and e-bikes (NACTO, 2020). Dockless micro-mobility services provide a flexible, effortless, and fast alternative for short-distance travel. Dockless micro-mobility services are substantially impacting mobility in many cities worldwide (Kopplin, Brand, & Reichenberger, 2021; Zhou, Ni, & Zhang, 2018): they could be a potential sustainable mobility alternative, potentially facilitating car-lite/no-car households and walkable neighborhoods in US cities. A 2019 survey reported that 45% of dockless trips replaced trips that would have been completed by personal/rider hailing vehicles (NACTO, 2020).

Micro-mobility can be a flexible complement for other traditional transportation modes, such as public transit and parking. Shared micro-mobility services are a presumptive solution to the first-mile and last-mile (FM/LM) problem for accessing public transit (Baek, Lee, Chung, & Kim, 2021; NACTO, 2020). Shorter trips can help scooter users start or finish longer transit trips (Lee, Chow, Yoon, & He, 2021; Smith & Schwieterman, 2018), and density of transit stations correlates with scooter usage (Bai & Jiao, 2020; Jiao & Bai, 2020; Merlin, Yan, Xu, & Zhao, 2021). A major dockless scooter provider, Lime, reported that 50% of the riders used it to reach public transit in June 2019 (Lime, 2019a).

Despite the potential collaboration with the public transit, dockless micro-mobility has some limitations that can significantly hinder its practical and equitable usage as a complement to transit. First, scooters' spatial distribution is very uneven (McKenzie, 2019), which can limit scooter services' FM/LM benefits to small areas. Second, dockless services' high expense can hinder its application for underprivileged populations, making the service less equitable. In this context, scooters' monetary cost can be the major bottleneck for their usage, rather than

* Corresponding author at: Postal address: 154 North Oval Mall, Columbus, OH 43210, USA.
E-mail address: liu.6544@osu.edu (L. Liu).

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their battery life or physical accessibility limits. Last, the asymmetrically low capacity of scooters can limit its collaboration with public transit. Dockless vehicles can only support one passenger per trip, while buses and trains have much higher capacities. This means that multiple scooters should be available at the same time and the same location if multiple users aim to finish a multimodal trip simultaneously. These three limitations can significantly limit the usability of the dockless systems as a complement to public transit.

To date, there are no studies systematically analyzing dockless micromobility's impacts on transit's afforded accessibility despite its rising popularity among the public. As concerns grow over dockless systems' possible negative impacts on cyclist and pedestrian road usage (Oeschger, Carroll, & Caulfield, 2020; Shah, Aryal, Wen, & Cherry, 2021), there is an urgent need for scientific understanding of dockless service's mechanism and strategic planning of a balanced e-scooters fleet. Therefore, understanding dockless systems' contribution to transit accessibility is imperative for evidence-based policy and planning for public transit authorities and scooter vendors.

The paper addresses the relationships between micromobility and public transit with following five research questions:

- RQ1: Can dockless micromobility service increase public transit accessibility? Are there differences between first mile and last mile?
- RQ2: Which parts of the transit system benefit most from the dockless micromobility service? How does dockless micromobility service's distribution policy impact the outcome?
- RQ3: Which parts of the dockless micromobility service contribute most to the transit system?
- RQ4: What is the impact of dockless scooters' monetary cost on its potential accessibility benefit?
- RQ5: What is the impact of dockless scooters' low capacity on its potential accessibility benefit?

To address these questions, we measure the impact of micromobility services on public transit accessibility – the *accessibility increment* – as the amount by which public transit accessibility improves due to the micromobility service. We develop separate measures for the first mile and last mile legs of a public transit journey, reflecting the differential impact of micromobility in these domains. We also address the uneven spatial distribution (RQ2 and RQ3), high monetary expense (RQ4) and limited capacity limitations (RQ5) mentioned above: We first investigate the impacts of scooters' distribution policy, including average distance from bus route, number of scooters, and degree of dispersion. We moreover study the impacts of monetary costs on increment as a measure of high cost's impacts on increment. We also develop concepts and measures of *capacitated accessibility increment*, reflecting the constraints imposed by the low capacity of micromobility. We illustrate these measures using real-time bus location data and scooter availability data in Columbus, Ohio.

In the next section, we provide a background for the accessibility increment measure and analysis. In the method section, we introduce our data source and define the accessibility measure and scooters' contribution to transit accessibility. In the result section, we use the accessibility increment measures to conduct stop-based and scooter-based analysis and tackle the three limitations above. We discuss the findings with practical guidance on the transit and micromobility planning, and steps for future research and conclude the paper.

2. Literature review

We introduce the scientific background from three perspectives: 1) the development of transit accessibility; 2) first mile and last mile problem and prior solutions; 3) dockless micro-mobility.

2.1. The development of transit accessibility

Accessibility is a fundamental concept in transportation science (Hansen, 1959; Ingram, 1971) and is especially crucial for public transit due to its collective and time-dependent nature. Because of shifts from traditional transportation planning to a sustainable mobility paradigm, transit accessibility is becoming more important as a measure to guide policy and system design (Banister, 2008). The measurement of transit accessibility has transformed from simple to realistic indicators with advances in data collection and analysis (Malekzadeh & Chung, 2020). Early transit accessibility models consider walking to transit stops as the only measure of transit accessibility (Hsiao, Lu, Sterling, & Weatherford, 1997; Zhao, Chow, Li, Ubaka, & Gan, 2003). This simplification helps to reduce the large computational load when calculating accessibility; however, since it ignores in-vehicle travel time and system performance it is a limited measure. With more available datasets on transit network and higher computational power, recent accessibility models adopt more realistic models. Examples include system-facilitated models that measure accessibility to reach other opportunities transit network (Tribby & Zandbergen, 2012) and integral accessibility models that calculate general accessibility to a number of possible destinations (Farber, Bartholomew, Li, Páez, & Habib, 2014; Owen & Levinson, 2015). Another trend in measuring transit accessibility is using more real-time or in-situ data instead of static data. Most traditional accessibility research used static schedule data due to the lack of real-time vehicle location data. Wessel, Allen, and Farber (2017) and Wessel and Farber (2019) used retrospective real-time transit vehicle location data to demonstrate that scheduled data overestimates the accessibility of transit systems. L. Liu, Porr, and Miller (2022), moreover, pointed out both schedule and retrospective real-time measures overestimates public transit accessibility and can be unreliable for public transit users.

The discussion above reflects a general trend for accessibility analysis: more realistic representation of travelers' behaviors using high-resolution data and more refined analysis. In this paper, we use real-time transit vehicle location data combined with a more precise approach to calculate more realistic measures of transit-afforded accessibility.

2.2. Solutions to transit system's first mile and last mile problem

The first mile and last mile (FM/LM) problem in public transit refers to the difficulties of starting and finishing the first and the last leg of a transit trip. Typically, transit trips start and end with walking; consequently FM/LM access can be a bottleneck for the whole trip (Wang & Odoni, 2016). Due to its importance for public transit ridership, numerous studies proposed solutions to the FMLM problem. We categorize these into two types: transit-based and multimodal-based solutions.

Transit-based solutions use optimization methods to assess and adjust the transit system itself to minimize the inherent FM/LM cost. Mohiuddin (2021) reviewed several strategies to reduce FM/LM cost adopted by various transit authorities, such as stop/station assignment, micro-level detail design, and integration of suburban and rural services. However, it is very hard to completely solve FM/LM problem for everywhere by only planning or optimization for fixed-route transit systems. Instead, most transit systems aim to improve FM/LM connections for underprivileged communities to promote transportation equity (Boarnet, Giuliano, Hou, & Shin, 2017; Mohiuddin, 2021).

Multimodal-based solutions use other mobility services to connect to public transit. Prominent examples are bike-sharing services (Kong, Jin, & Sui, 2020; Z. Liu, Jia, & Cheng, 2012; Shaheen & Chan, 2016), ride hailing services (Brown, Manville, & Weber, 2021; Huang, Kockelman, Garikapati, Zhu, & Young, 2021), and autonomous vehicles (Chong et al., 2011; Moorthy, De Kleine, Keoleian, Good, & Lewis, 2017). There are three prerequisites for a multimodal-based solution as a viable alternative to walking: 1) *high flexibility* – the solution itself does not have its own FM/LM access concerns; 2) *low dependency* – the solution does not take a large additional amount of time to use, such as when unlocking or parking; and 3) *higher speed* – the solution saves time compared to walking. However, a FM/LM solution can also compete with the connected transit system by modal substitution that induces unwanted modal shifts that undermine transit (Gehrke, Felix, & Reardon, 2019; Kong et al., 2020). Therefore, a major focus for FM/LM research is to investigate the degree of collaboration versus competition between the public transit and the FM/LM service.

Among these potential solutions, bike-sharing services attracts much attention for its low negative externalities, such as air quality impacts (Otero, Nieuwenhuijsen, & Rojas-Rueda, 2018) and low operational carbon footprint (Zhang & Mi, 2018). Martens (2004) studied the bike-and-ride trips in European cities and concludes that FM/LM connections favor faster modes of public transit like trains. Campbell and Brakewood (2017) examined the competition between bike-sharing and public transit and found a small yet potentially significant negative impact on travel behaviors and transit ridership. Kong et al. (2020) investigated three possible relationships – i.e., modal substitution, integration and complementation – between bike-sharing and public transit and concluded that modal integration or FM/LM connections happen more during shorter trips, subscribers, and weekdays.

2.3. Dockless micro-mobility

Dockless micro-mobility services satisfy the three prerequisites for walking alternative in the first and last mile (high flexibility, low dependence and higher speed). Therefore, vendors promote dockless micro-mobility services as a potential solution to the FM/LM problem, especially for urban public transit systems (Association American Public Transportation, 2019; Bird, 2019; Lime, 2019b). Baek et al. (2021) points out the travel time and psychological benefit of e-scooter service compared to walking and showed that e-scooter sharing service can be a competitive last-mile mode.

Several studies investigate the potential collaboration between dockless micro-mobility and public transit. For example, Jin, Cheng, Li, and Hu (2018) found the correlation between subway traffic increase and dockless bike-sharing increase due to their complementary effect in Beijing, China. Zhou et al. (2018) found dockless bike-sharing is the second most selected mode to connect to metro but mostly replaced walking and bus trips in Shanghai, China. Kopplin et al. (2021) surveyed e-scooters users in Paris, France and concluded that e-scooters replace walking instead of other transportation modes. Yan et al. (2021) moreover measured that about 10% of e-scooter trips are to connect with metro in Washington DC, USA. On the other hand, Luo, Zhang, Gkritza, and Cai (2021) concluded that e-scooter services can compete with bus service and result in bus ridership reduction in Indianapolis, USA. Results from transit systems with higher frequency and metro systems show stronger collaboration effect between the two modes, which is consistent with prior findings of docked bike-sharing services (Campbell & Brakewood, 2017; Ma, Liu, & Erdoğan, 2015; Martens, 2004).

There are still unanswered scientific questions regarding micro-mobility and public transit. First, most prior studies focused on the usage of multimodal trips, rather than useability; very few studies address the impacts of dockless micro-mobility services on transit system's afforded accessibility and transit FM/LM problem. Second, the mechanisms of dockless service's impact on transit accessibility are not well understood. Finally, most studies were conducted for subway and light rail systems or other types of high-frequency transit service: the relationships with lower frequency bus service are not understood. We address these gaps in this paper.

3. Method

In this section, we first introduce the two major data sources in this study. We then define the accessibility measure used in the paper and the *accessibility increment* – this measures the contribution of dockless micromobility to transit accessibility. We also introduce corresponding spatiotemporal analyses to address the three limitations of dockless micro-mobility.

3.1. Data

We use three main datasets in this paper: i) General Transit Feed Specification (GTFS) data for public transit; ii) the locations of available of dockless vehicle from a common micro-mobility service, and; iii) the empirical transit usage data in 2019 from StreetLight (StreetLight, 2021). Our study area is Columbus, Ohio, USA: a mid-sized city with a bus-based public transit system.

3.1.1. GTFS data

Many public transit authorities publish schedule and real-time vehicle location using the GTFS data standard; these data enable consumer mapping and navigation applications. The GTFS data consists of two standards: *GTFS static* and *GTFS real-time expansion*. GTFS static reports the schedule data for a public transportation system and is now the de facto standard for public transportation schedules and associated geographic data (Google Developers, 2020). GTFS real-time data moreover provides vehicles' arrival and departure time at every sequential stop in a homogeneous format. We collected the GTFS real-time data from Central Ohio Transit Authority (COTA) in Columbus, Ohio from June to December 2019 in the interval of 1 min, which is a common information updating frequency for transit systems in the US (Liu & Miller, 2020a).

3.1.2. Real-time available e-scooter data

Most micro-mobility sharing services rely on a dedicated smartphone app platform to provide real-time information of nearby available (unoccupied) dockless vehicles for users. Many of these services have application programming interfaces (API) for programming purposes. These data contain the location, remaining battery and remaining miles numbers for users to travel, last updated time, and a partly obfuscated ID of each available scooter. For every update with frequency of 1–2 min, a scooter will be removed from the feed data when it is unlocked by a user or collected by administrators. We collected all the available dockless vehicle's location data from Lime scooter, a major dockless scooter provider, from June 20th to December 20th, 2019.

3.1.3. Empirical public transit usage data

We use a time-based weighted accessibility measure to account for public transit patronage in our analysis (see Eq. (3) below). We acquired empirical public transit usage data in 2019 from Streetlight, a third party mobility data vendor that provides transportation traffic data derived from mobile phones and proprietary machine-learning algorithm (StreetLight, 2022). The data consists of traffic flows by public transit from and to every census blockgroup in the county of Franklin, Ohio. Since most analyses in this paper is stop-based, we then calculate the stop-based OD matrix by evenly dividing each traffic flow per number of stops in a blockgroup.

3.2. Accessibility increment

The speed and range of micromobility influence their incremental impact on public transit accessibility. We use 4.5 m/s or 10 mph as a typical average speed of scooters (Lime, 2021; Razor, 2021), which is significantly higher than walking's 1.4 m/s (Browning, Baker, Herron, & Kram, 2006). Since scooters can also travel further than walking, this can help public transit users choose different bus stops and routes, with advantages such as avoiding route transfers. Fig. 1 shows an example drawn from COTA GTFS data. The red and blue trajectories are the bus trip with and without the presence of scooters, respectively. The user can

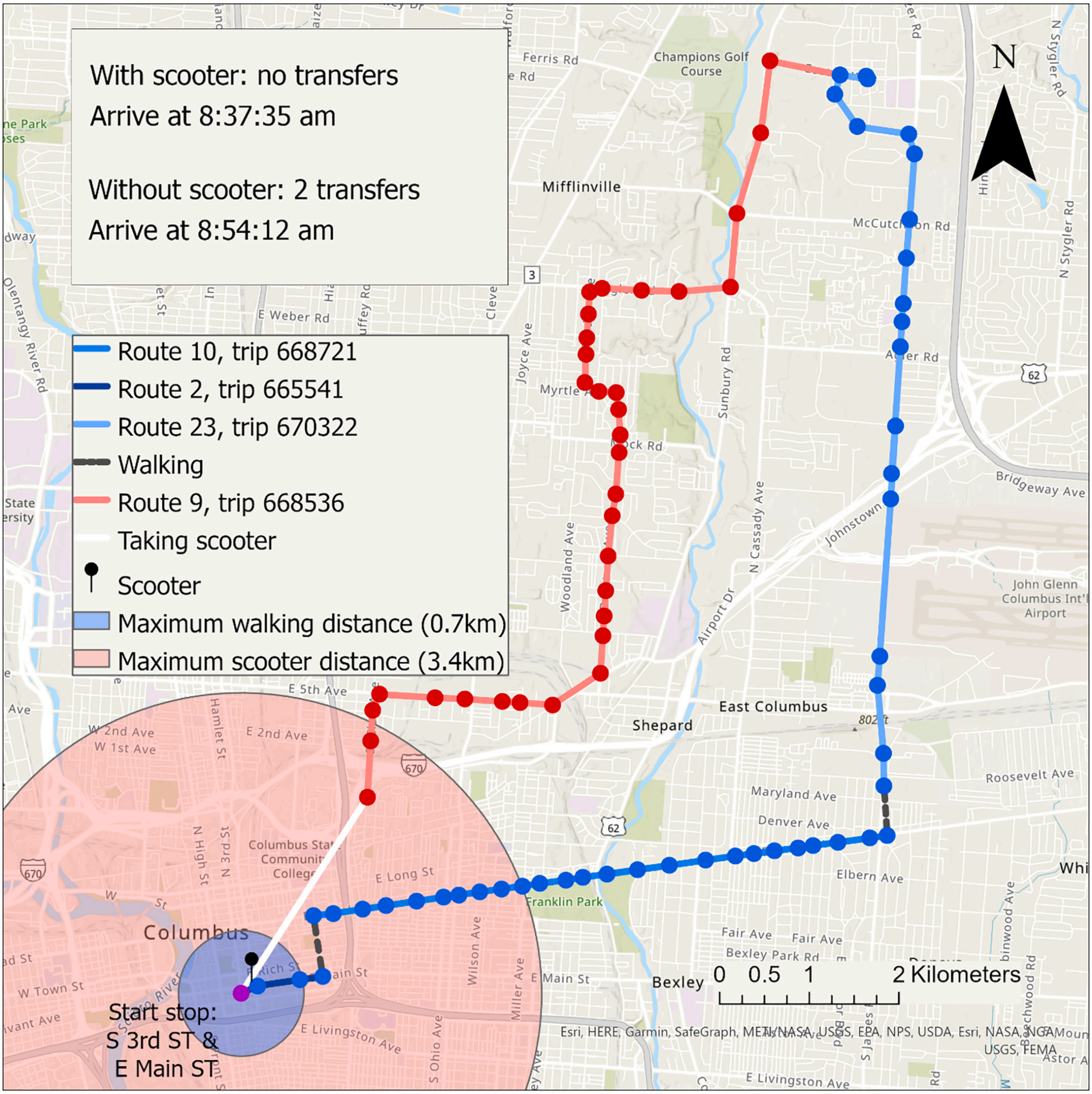

Fig. 1. An example of transfer skipping in the first mile with the presence of scooters and longer maximum reachable distance.

travel faster and further after introducing the scooters in the transit system, therefore avoid longer trip and transfers to get a direct trip to the destination. Notice that the maximum scooter distance is also dependent on scooter users' willingness to pay: since scooters charge by time, money buys distance. In our analysis, we assume that people do not use scooters to make transfers and instead rely on walking if necessary as most bus route transfers occur at the same stop or between proximal stops (Hadas & Ranjitkar, 2012).

To address RQ1, we use a travel time-based measure to quantify transit accessibility in this paper: shorter travel time between the origin and other stops indicates the origin has higher degree of accessibility. Compared to accumulative opportunities or area, it is much easier to decompose and therefore calculate the contribution of different scooters in the first mile and last mile. We introduce *accessibility increment*, which measures the bus system's accessibility improvement generated by the micro-mobility service. It measures how much total time a scooter can save for a transit-scooter user, inclusive of first mile access, in-vehicle travel, any transfers and last-mile egress. The total accessibility increment will include up to two components depending on the availability of dockless vehicles around: the first-mile increment and the last-mile increment, which is generated by using a dockless vehicle before and after the bus trip, respectively.

For every hypothetical trip from and to every stop, we calculate the first-mile accessibility increment by:

$$a_{ij\tau}^{(\alpha)} = A_{ij\tau}^{(\alpha)} - A_{ij\tau} \tag{1}$$

where: $a_{ij\tau}^{(\alpha)}$ is the accessibility increment generated by a dockless vehicle

α in the *first mile* from station i to station j from start time τ. $A^{(\alpha)}_{ij\tau}$ is the accessibility measure (based on shortest travel time) between stop i and j when taking the dockless vehicle α in the first mile. Notice we calculate last-mile increment separately later, so there is no last-mile scooter involved in the calculation of first-mile increment. $A_{ij\tau}$ is the accessibility measure without the dockless vehicles' aids. The first-mile increment is nonlinear due to the nonlinearity of transit system; for example, a user can save no time even if she/he arrives at the stop early by taking a scooter, since the user still needs to wait for the bus. Therefore, the total saved time generated by the scooter is not necessarily the same as the time the scooter saves compared to walking.

We then define the last-mile accessibility increment, which is the saved travel time during the final trip segment:

$$a^{(\beta)}_{ij\tau} = A^{(\alpha,\beta)}_{ij\tau} - A^{(\alpha)}_{ij\tau} = t^{s,\beta}_{w} + t^{\beta,d}_{s} - t^{s,d}_{w} \tag{2}$$

Where: $a^{(\beta)}_{ij\tau}$ is the accessibility increment generated by the dockless vehicle β in the *last mile* from station i to station j from start time τ. $A^{(\alpha,\beta)}_{ij\tau}$ is the accessibility measure between stop i and j with the help of scooter α and β and $A^{(\alpha)}_{ij\tau}$ is the measure with only help of scooter α. $t^{s,\beta}_{w}$ is the walking time between the offboarding stop and the scooter, $t^{s,d}_{w}$ is the walking time between the stop and the destination, and $t^{\beta,d}_{s}$ is the dockless vehicle riding time between the scooter and the destination. The last-mile increment is linear since it is the last part of the whole trip; it can be easily calculated by subtracting the travel times from the off-boarding bus stop to the destination by foot and by the dockless vehicle. Fig. 2 provides an illustration. Notice that there is a chance of last-mile increment being negative, meaning taking the scooter may increase travel time for the user. These cases are undesired for users and can be easily predicted and filtered out by trip planning apps or scooter apps before the trip due to the linear nature of the process; in other words, the apps can recommend the users to use the scooter only when it would save time for them. Therefore, we eliminate those cases so that all the recorded increments are positive to simulate the decision-making process of trip planning apps or users.

To address RQ2 and RQ3, we aggregate the increments based on stops and dockless vehicles' location. Due to the nature of saved travel time and its definition, the accessibility increment is additive. First, we define a weighted average accessibility increment to address RQ2:

$$a_{i\tau} = \frac{\sum_{j\in D} M_{ij}\cdot a_{ij\tau}}{\sum_{j\in D} M_{ij}} \tag{3}$$

Where: M_{ij} is the weight. D is the collection of all destination stations, which is selected from all the stops in the system. The destination

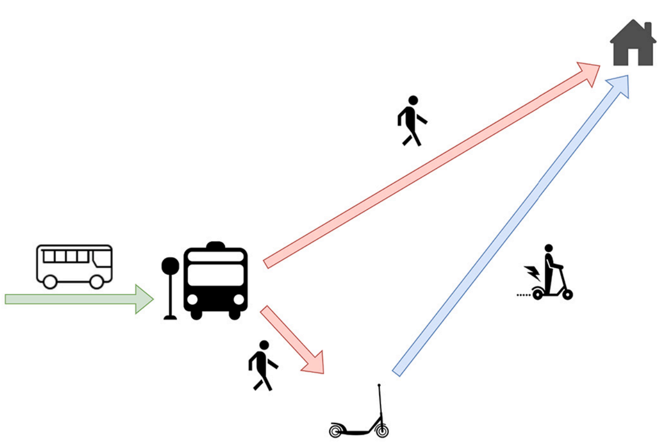

Fig. 2. An example of last-mile increment (red: walking trips with slower speed; blue: dockless vehicle trip with higher speed; green: bus trip with highest speed). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

collection D will be a subset of all stops because there are some stops have very low connectivity, which make other stops nearly impossible to access them. Eq. (3) is similar to the weighted average travel time measure (see below).

We derive the weights M_{ij} for every origin-destination pair (i, j) from empirical data. We use the origin-destination (OD) matrix of public transit trips for every day in four months in 2019. The OD matrix data are collected from StreetLight, a mobility data company that tracks population movement with mobile phone data. Ideally, the weights should be based on the OD Matrix for each day; however, because the empirical OD matrixes can be very sparse due to low ridership and large number of stops and the results can be easily influenced by unusual outlier trips, we aggregate all the trips in four months to a single OD matrix and use the same matrix for every day.

To address RQ3, we aggregate the increments per scooters' location. In practice, we use 35 m-by-35 m grid cells: we aggregate all the scooters' increment to each grid cell according to their real-time location when the multimodal trip happens. Each cell's first-mile and last-mile increment contribution is:

$$a_{\gamma\tau} = \sum_{i\in S}\sum_{j\in S} M_{ij}\cdot a^{(\gamma,*)}_{ij\tau} + \sum_{i'\in S}\sum_{j'\in S} M_{i'j'}\cdot a^{(*,\gamma)}_{i'j'\tau} \tag{4}$$

Where: $a_{\gamma\tau}$ is the total accessibility increment generated by the dockless vehicles in the cell γ, $a^{(\gamma,*)}_{ij\tau}$ is a trip's first-mile accessibility increment boosted by a dockless vehicle in the cell γ, and $a^{(*,\gamma)}_{i'j'\tau}$ is a trip's last-mile accessibility increment boosted by a dockless vehicle in the cell γ. The first item of the formula represents all first-mile increment contributed by the dockless vehicles in the cell while the second item represents all last-mile increment. It can represent the total contribution of all the dockless vehicles in a grid cell to the accessibility of a transit system in a specific timestamp τ.

3.3. Accessibility measure

We use weighted average travel time (WATT) – the average travel time from the start stop to all the other bus stops weighted by ridership or population – to calculate accessibility (Fayyaz, Liu, & Zhang, 2017):

$$T_i = \frac{\sum_{j\in D} M_{ij}\cdot t_{ij}}{\sum_{j\in D} M_{ij}} \tag{5}$$

Where: T_i is the weighted average travel time of station i, M_{ij} is the weight, t_{ij} is the shortest travel time between stop i and stop j.

We conceptualize the bus system as a directed graph and bus stops as nodes, with the total travel time between the stops as costs. Any links in the graph can be finish by one of the three ways: 1) walk by foot if distance is smaller than 700 m, 2) wait and taking transit, or 3) walk and take a scooter if the link is the first or last leg of the whole trip and the scooter trip does not exceed five dollars and the scooter's battery life.

To calculate the shortest time and path from the start location to each bus stop in the system, we develop a time-dependent Dijkstra's algorithm to solve for public transit routes based on the GTFS real-time data. *Time-dependent* means that the user's travel time depends on their arrival time at a bus stop (Gendreau, Ghiani, & Guerriero, 2015). This also means that the travel time cost for each link is dynamic, with a high computational load. Because Dijkstra's algorithm can only be applied to network with static weights, we introduce a *first-in-first-out (FIFO)* or *no-passing* rule to make it compatible with a time-dependent network (Ahn & Shin, 1991; Ichoua, Gendreau, & Potvin, 2003). FIFO rule assumes that any vehicles leaving a stop will not arrive later at a subsequent stop than a vehicle that departed later. Using the GTFS data, we empirically tested that 95% of bus trips in the COTA systems satisfy the FIFO rule, meaning the assumption is applicable.

After optimizing and parallelizing the algorithm, we can calculate OD matrices with 9 million flows from and to all stops (~3000) in the

COTA bus system in 3 h. We calculate all the travel times from and to every stop in the COTA system with and without the Lime micromobility service in Columbus, Ohio at 8 am for every day from July to December 2019. The size of OD matrixes database in MongoDB is more than 1 terabyte. We also derive each dockless scooter's first-mile and last-mile increment in each flow between all bus stop pairs. We then aggregate the increment with respect to their origin, destination, and the scooter used in each flow; the aggregations are weighted by numbers of empirical public transit trips in 2019. We aggregate first-mile and last-mile increments according to their origin stop and destination stop, respectively.

To answer RQ2, we calculate stop-based increment, which measures the average merits (i.e., saved average travel time from the stop to other stops) from the scooter service received by each stop. We also calculate scooter-based increment for RQ3, which measures the total merits provided by each scooter.

3.4. Economic cost sensitivity analysis

An equity challenge to dockless micro-mobility's useability is its high out-of-pocket cost. Dockless scooter is less affordable than public transit; meanwhile, the physical maximum reachable distance is directly proportional to the fee a user can pay due to a fee per unit time. As the reachable distance increases, a user can sometimes skip some transfers in their trips, which is a major source of unreliability and additional waiting time (Liu & Miller, 2020b).

For the case of Columbus, public transit costs two US dollars with unlimited transfers in 2 h, while Lime scooters requires one dollar to unlock and 0.32 US dollars per minutes to use. There are some reports on the mean length of single scoter trips from 1.2 km or 7.55 min in Austin (Jiao & Bai, 2020) to 0.6 km or 5 min in Washington DC (McKenzie, 2019); however, research on scooter users' willingness to pay and maximum travel distance is still lacking. To investigate the impacts of economic cost (RQ4), We therefore conduct a sensitivity test on the economic cost (or maximum reachable distance) from 2 US dollars (0.8 km) to 12 US dollars (9.2 km) with interval of 1 US dollar (0.8 km) in a typical day. Notice we use 5 US dollars as a default maximum limit of people's willingness to pay in a single leg of a multimodal trip.

3.5. Capacitated accessibility increment

Low capacity is a major limitation of all dockless micromobility services: dockless vehicles can only carry one person under normal operating conditions. However, public transit systems usually have much larger capacity than micromobility systems. This imbalance can make capacity a major bottleneck for the potential collaborations between public transit and micro-mobility.

The ordinary version of accessibility (WATT) and accessibility increment can be considered as first-order measures, since all the mobility are assumed to be finished by one person and the user only needs one dockless vehicle during any trip. This does not capture situations when multiple people try to conduct the same trip. To address this issue, we introduce the concepts of *higher-order accessibility* and *higher-order accessibility increment*, the capacitated version of each accessibility measure. For example, a Nth-order accessibility measure captures the joint accessibility of N persons trying to complete their trips simultaneously. The measures can also be understood as the same accessibility measures without the nearest (N-1) dockless vehicle's aid because they are already occupied by other users. If there is not enough available dockless vehicle near the starting position, the accessibility measure should be the same as the one without any dockless vehicles' helps.

To address the impacts of capacity (RQ5), we introduce two versions of capacitated higher-order accessibility based on two different scenarios: *collaboration* and *competition*. With collaboration, several people will try to finish the trip and strictly stay together: if there is not enough dockless vehicles available, the users will not use micro-mobility; the travel time of the whole group will be the travel time of the slowest person in the party. A real-world example is a group of friends who will attend an event at a same time and same location. With competition, travelers do not need to keep synchronized; therefore, they can find the best option for themselves. However, since the amount of dockless vehicles are limited, they must compete with each other; the average travel time of the whole group will be the mean of all people's travel time. A real-world example is a group of strangers who happen to be at the same location and want to use scooters at the same time. The collaboration scenario is stricter than the competition scenario.

4. Results

4.1. Stop-based increment

The first-mile increment significantly outweighs its last-mile counterparts. From July to December 2019, the average first-mile increment – the average saved time by using scooters in the first mile when traveling from a stop to all other stops – is 249 s (median = 225 s, standard deviation = 201 s). The average last-mile increment – the saved time by the scooters at other stops to reach a stop – is 8 s (median = 1.3 s, standard deviation = 12 s). This demonstrates that first-mile scooters can save a lot of time for later legs by catching an earlier bus or skipping a transfer thanks to the nonlinearity of public transit systems as we discussed in Section 3.2. However, compared with the WATT without the micromobility service (2093 s), there are still room for improvement. Fig. 3, moreover, visualizes the travel time composition with and without the micromobility service; despite significant improvement, the portion of travel time by scooter is still relatively small. Travel time by public transit is still the major determinants of total travel time in a scooter-transit multimodal trip.

First- and last-mile incremental accessibility also have different spatial patterns. Fig. 4 shows the spatial pattern of the first-mile increment by origin stops (left), last-mile increment by destination stops (right). Both increments are clustered to the center of the city where most available scooters are present, while last-mile increment is even more clustered.

To address the connection of accessibility increment and micromobility service's distribution policy in RQ2, Fig. 5 shows the relationship between the number of available scooters and first mile (left) and last mile (right) accessibility increment. In general, larger accessibility increment correlates with more available scooters, as expected. However, note in both cases there is a separate cluster with additional scooters and but relatively low contributions to accessibility increment; these data points corresponding to scooters added after 2019/11/15. To moreover investigate this phenomenon, we aggregate available scooters to 35 m-by-35 m cells and summarize the daily average number of available scooter as shown in Fig. 6. The figure suggests a change of vendor's distribution policy near 2019/11/15: it shows the number of scooters increased, but the additional scooters were more clustered and concentrated in fewer cells. This indicates that mere increase in the number of available scooters may not necessarily lead to corresponding improvements incremental accessibility for transit users if the additional scooters are not well distributed; accessibility increment favors a more dispersed spatial distribution.

To study the possible relationship between stop-based increment and distribution pattern (RQ2), we conduct a simulation of the point pattern of scooters. The primary factor is the average distance from the bus routes. We simulate ten different scenarios with 400 scooters; in each scenario the scooters have average distance of 50 m to 500 m from bus routes as shown in Fig. 7. The first-mile increment's pattern is uneven since the first-mile impacts are nonlinear, while the last-mile increment decreases as the scooters' distance from bus routes increases. This suggests that it is hard to directly predict and improve the increment in the first mile by changing the scooter distribution strategy, while last-mile increment is small but easier to improve. Meanwhile, from the

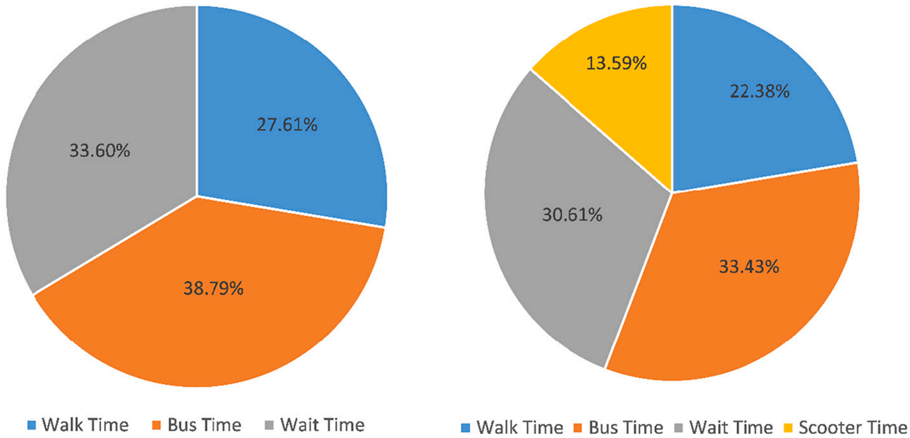

Fig. 3. Travel time composition without (left) and with (right) the micromobility service.

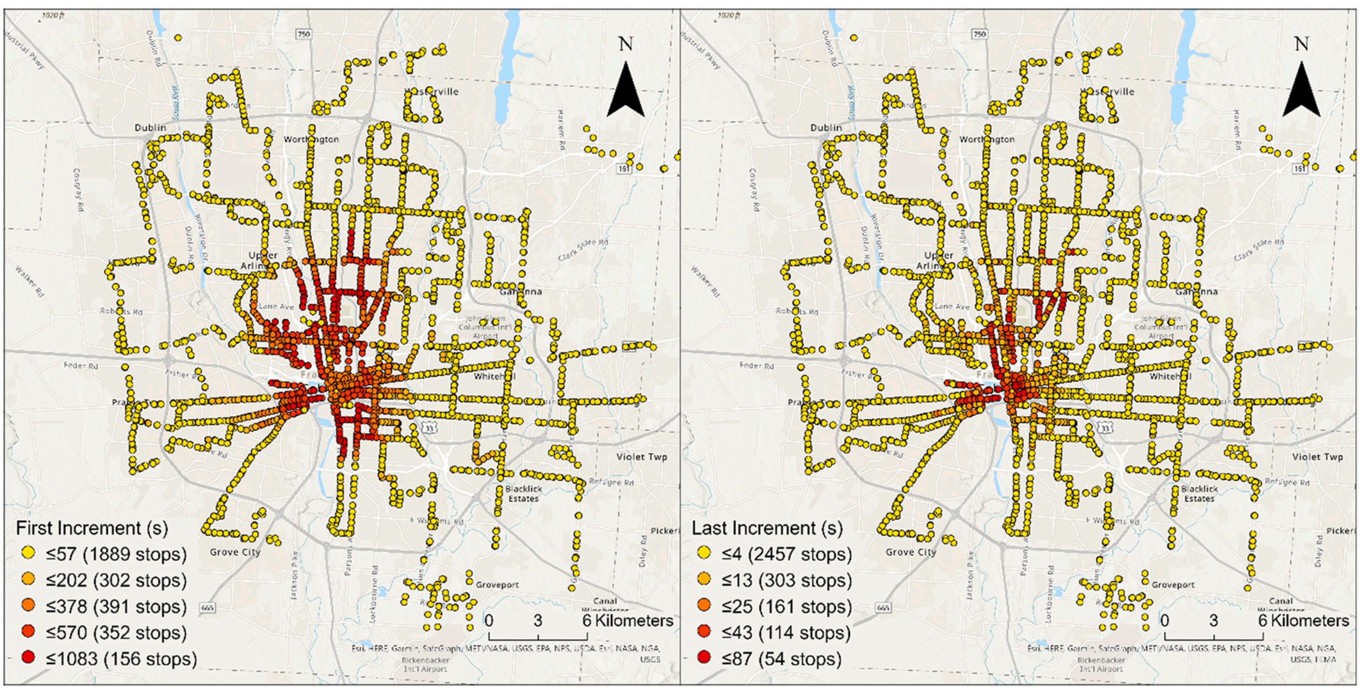

Fig. 4. Average accessibility increment by first-mile (aggregated by origin stops) and last-mile (aggregated by destination stops) with Jenks natural breaks classification.

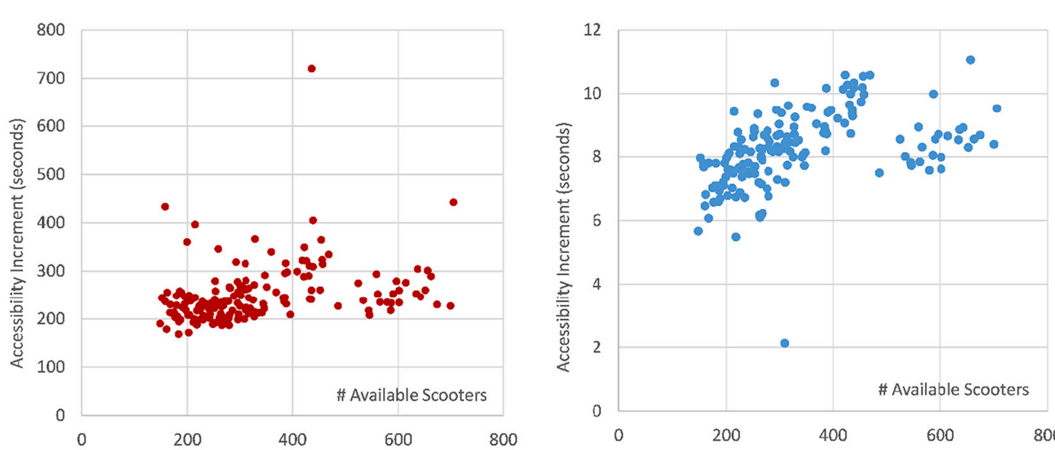

Fig. 5. Relationship between average number of available scooters and the first-mile (left) and last-mile (right) accessibility increment.

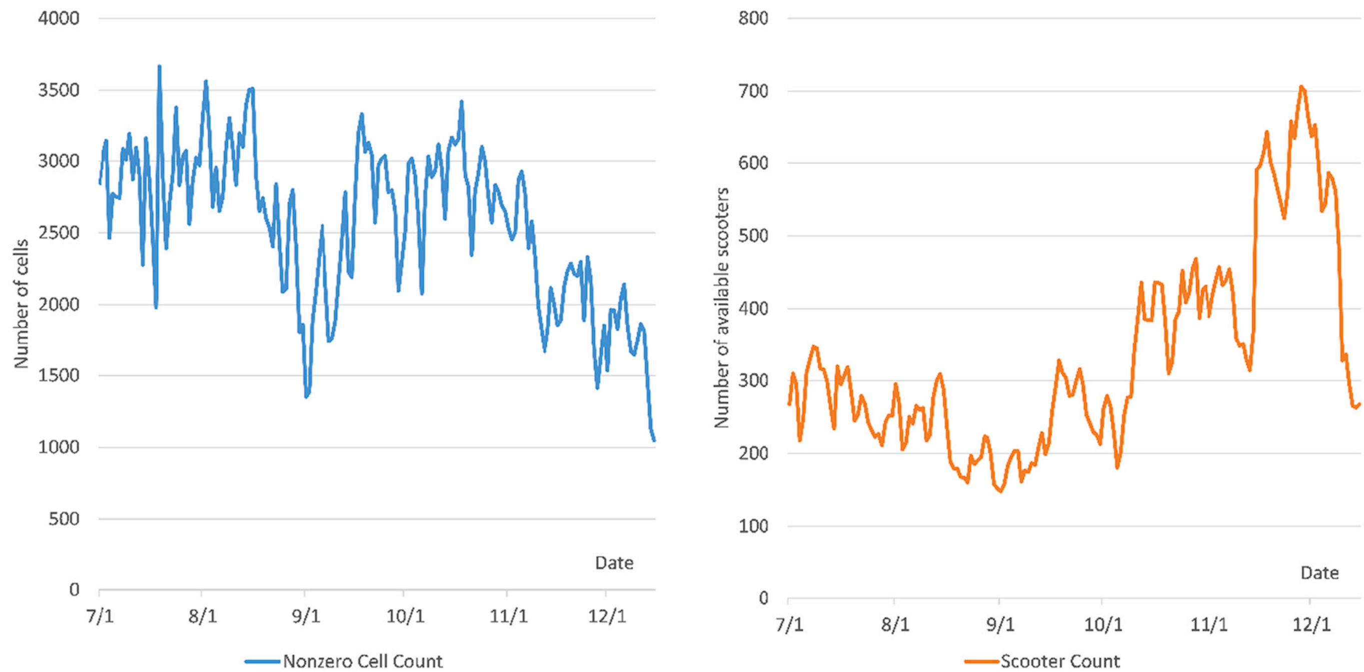

Fig. 6. Number of cells without any scooter presence and daily number of average available scooters.

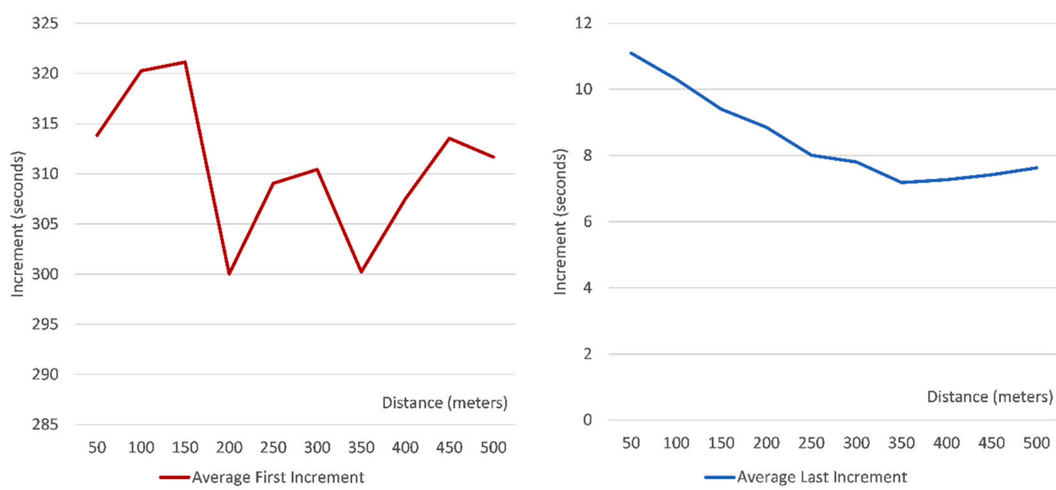

Fig. 7. Average increment in the first and last mile for each scenario with average distance of 50 to 500 m from COTA routes. Note the scales are different.

perspective of demand, it is also much easier to promote last-mile trips because their start is much predictable (i.e., bus stops). Although first-mile and last-mile trips create equal economic revenue and vendors may tend to focus on the last mile, it is imperative to point out that first-mile trips can create much more accessibility opportunities for users.

4.2. Scooter-based increment

To answer RQ3, we aggregate *total* accessibility increment per each scooter as an absolute measure of their merit using Eq. (4), which represents the scooters' contribution to the entire transit system. We calculate the daily Gini coefficient of total increment as an indicator of inequality of each scooter's contribution to the transit system. Gini coefficient ranges from 0 to 1; it measures the degree of inequality in a distribution. Higher Gini coefficient means the distribution of scooters' total accessibility increment is more uneven. The first-mile increment's average daily Gini coefficient is 0.62 while last-mile increment's is 0.69. Both Gini coefficients are high, which means the majority of accessibility increment is from a small number of scooters and their locations. Scooters' total first-mile increment is slightly more equal than the last-mile increment per Gini coefficients. Notice that we do not argue increment contribution in all cells should be even; instead, actual demand for scooters and multimodal public transit trips should be the primary factors that influence the distribution policy.

We also aggregate each scooter's increments to 35 m-by-35 m grid cells per each scooter's location in each trip. The top 1% cells account for 58% of total first-mile increment and 72% of total last-mile increment. We, moreover, extract the top 1% grid cells with highest increment contribution and summarize according to their zoning types as shown in Fig. 8. Most contributions to the first mile came from residential and manufactured areas, while most contributions to the last mile came from downtown and residential areas. This, moreover, resonates with the spatial pattern in Fig. 4: last-mile increment is clustered around the city center and bus stops, while first-mile increment is relatively outspread.

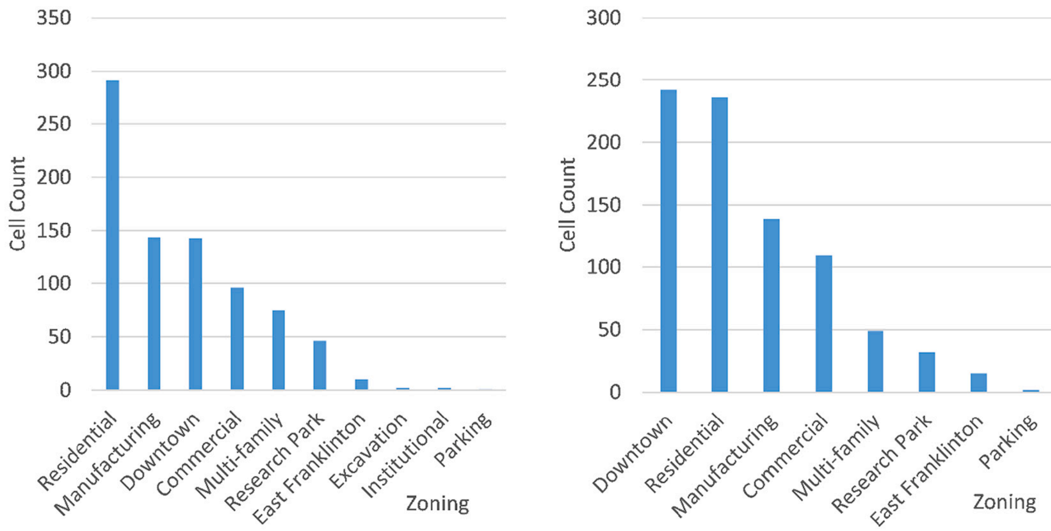

Fig. 8. Top 1% grid cells' zoning type for the first (left) and last mile (right).

4.3. Economic cost impact

To answer RQ4, we first show the relationship between accessibility increment and scooter fee limit in dollars in Fig. 9. We can see the first-mile increment rapidly decreases with greater cost as the possibility to save time in later bus trips decreases due to the nonlinearity of the public transit. However, due to the linear process of the last-mile increment, it slightly increases and stabilizes as maximum reachable distance decreases. This means that accessibility increment may not necessarily increase with higher willing to pay. This may be because longer last-mile scooter trips may be less competitive. The selection of only positive increment can also contribute to this change.

4.4. Capacity impact

The low capacity of scooter can have a major impact on the collective accessibility of a group of people who want to execute a multimodal trip at the same time. Therefore, to answer RQ5, we calculate capacitated increment with respect to the number of concurrent users per our definition in Section 3. Fig. 10 shows the two capacitated increments under the collaborating and competing scenarios. In both scenarios, the accessibility increments decrease rapidly with more concurrent users, especially among collaborating users. Fig. 11 compares the spatial distribution of scooters with the capacity-related accessibility loss with more concurrent users at the bus stop-level. The figure indicates a clear negative correlation between the two measures: the places with more available scooters tend to retain the accessibility benefit of scooters even with more demand. Higher scooter availability can promote more cooperative trips and remedy competition between users, which can generate large amount of economic revenue and accessibility increment. However, given the same number of scooters, a distribution that better satisfies concurrent demand runs counter to a more socially equitable distribution, as illustrated by the results mapped in Fig. 4.

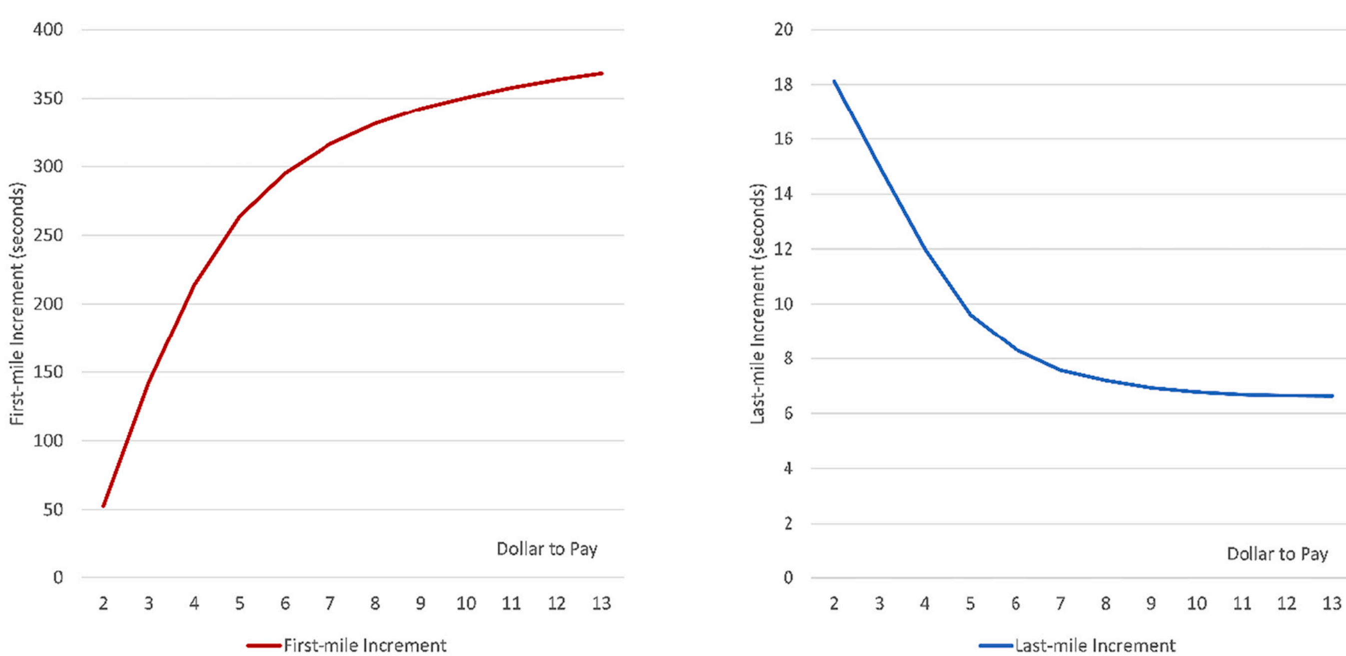

Fig. 9. First-mile and last-mile increment with different scooter fee limits.

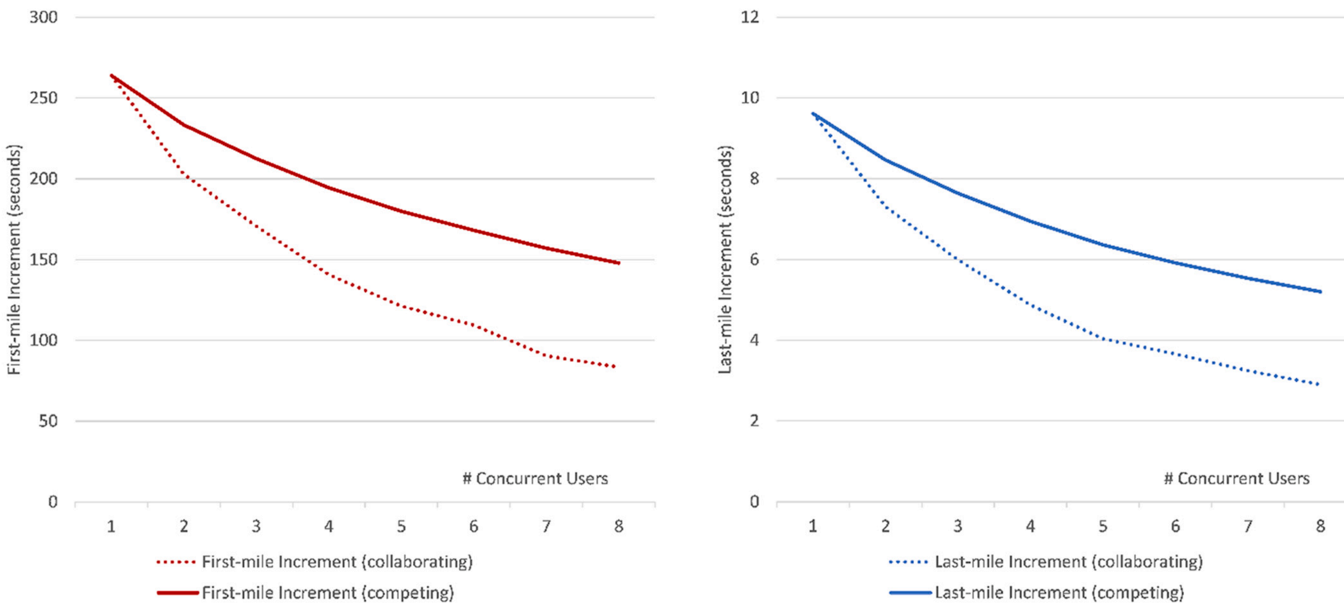

Fig. 10. The average first-mile and last-mile increment with respect to the number of concurrent users.

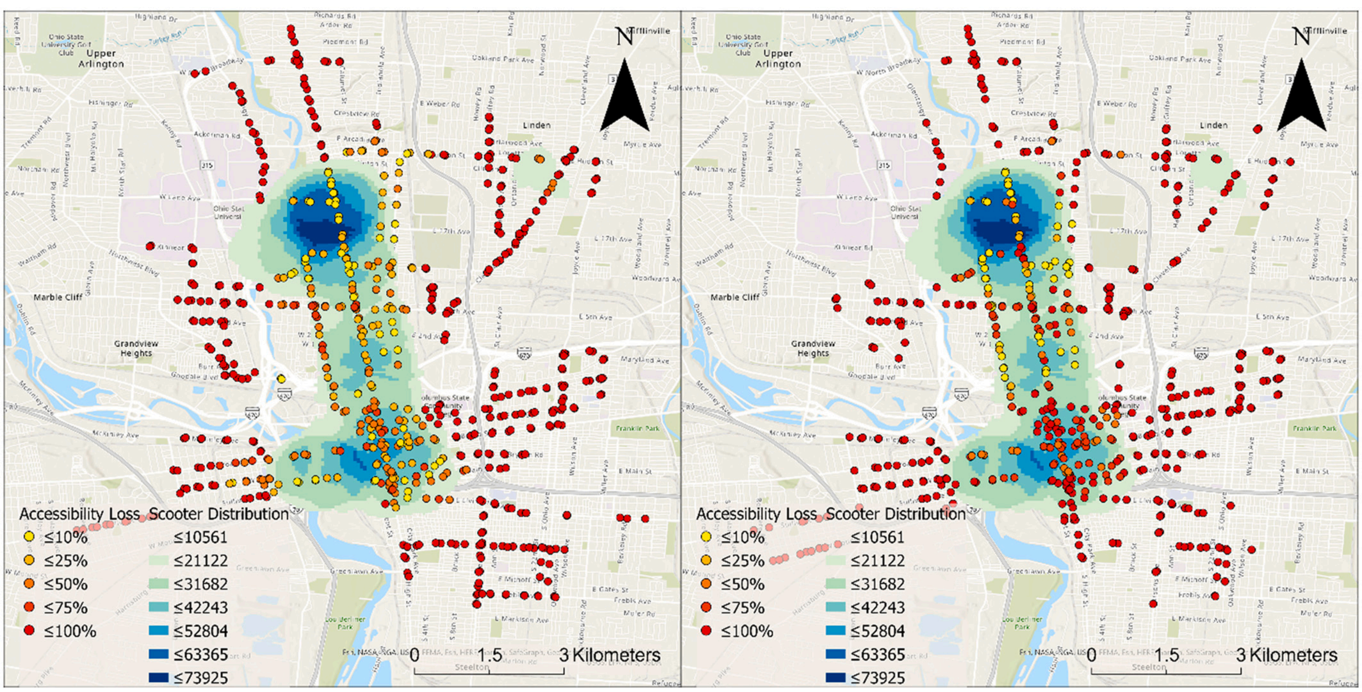

Fig. 11. Stop-level capacity-related loss in accessibility with respect to concurrent users and the point density distribution of available scooters.

5. Discussion

The flexibility, speed and low dependency of dockless micromobility services has potential to substitute for automobiles in short-distance trips. These services can also help address the first mile and last mile access problems for public transit trip. Despite its popularity, the impacts of the dockless scooter service on public transit accessibility still remain largely unknown. In addition, there are no rigorous measures for analyzing these impacts for applied policy and planning. To fill in these gaps, we use travel-time based accessibility measures to measure the public transit accessibility with the presence of dockless scooters. We introduce the concept and measurement of *accessibility increment* – the impact of first mile/last mile mobility services on transit accessibility. We conduct two major analyses based on the introduced measures: stop-based increment analysis, which represents the received merits from the scooter system for each transit stop, and scooter-based total increment analysis, which represents the provided merits by the scooter system.

We find dockless scooters can increase afforded accessibility by multimodal public transit trips, i.e., using scooters in the first and last mile of a public transit trip. The stop-based analyses show that the increment in the first mile significantly outweighs the last mile. We also observe both increments are highly clustered in the area with higher presence of available scooters and higher walkability. We, moreover, find out that although more available scooters are positively correlated with both increment, spatial distribution can also impact the increment. As vendors chose to distribute scooters with higher quantity but in a more clustered manner, the increment did not increase proportionately. Scooter-based increment analyses also show that a small number of scooters and cells that these scooters are in provided most of the benefits.

We also systematically analyze three limitations of scooters that can hinder its collaboration with public transit. First, scooters and their merits are limited to a very small and privileged area, suggesting injustice of current spatial distribution. Second, the high cost of dockless scooters makes it disproportionately expensive compared to public transit. The increment is proportional to the money paid; it is costly to maintain high increments, making it less practical for transit users and creating more disparities for low-income population. Last, dockless scooters' asymmetrically low capacity compared to public transit makes them more difficult to collaborate. With more concurrent users, the increment rapidly decreases and the places with less available scooters decrease faster. Compared with competing scenario where strangers compete for same scooters, a party of multiple friends requires higher availability and their average increment decrease faster.

The paper provides evidence for future transit and micromobility planning. First, although first-mile trips are much harder to predict and create same revenue per trip compared to last-mile trips, their accessibility increments are significantly higher than their last-mile counterparts. The rewarding is sizable if the first-mile demand is well predicted and realized. The last-mile increments can increase too as scooters become closer to bus stops according to our analysis, despite very little compared to first mile. The results can also guide the future distribution policy of scooter vendors. We know more scooters are correlated with both increments in general, and extra scooters in same places can maintain the merits of scooter service even with more concurrent users. However, this cannot justify the waste of resources and space; again, this calls for more refined demand prediction and balanced equitable optimization between potential conflicting objectives. For example, we find that more clustered spatial pattern can lead to disproportionately small increments, but more clustered pattern may also make scooter service more resilient to more concurrent users and promote more last-mile demand.

The study has limitations. We only address the useability of the scooters and the supply of transit accessibility, rather than the actual usage of the scooters and the demand of transit services. We justify the average waiting time by empirical public transit trip data; however, the multimodal transit trips may not be perfectly proportional to the total transit trips. We hope future research can continue the topic by examining the demand of multimodal trips with transit and scooters. Our study also simplifies sidewalk and scooter routing by using Euclidean distance because of the large computational overload discussed in the method section. This assumption may influence the outcome by different factors: first, it may overestimate pedestrians' ability to use transfers, which leads to higher transit accessibility and lower accessibility increment; on the other hand, it may also overestimate scooters' mobility merits due to the lack of compatible infrastructure for scooters. The differential impacts of infrastructure on scooter users and pedestrians warrant more discussion; future research can use actual sidewalk network and road network for scooter users for more realistic simulation. Finally, the paper uses retrospective real-time accessibility (Wessel et al., 2017; Wessel & Farber, 2019), which overestimates transit users' ability to use transit due to assumption of perfect knowledge on systems operations as they occurred (Liu et al., 2022).

6. Conclusion

This paper investigates the impacts of micromobility service on public transit system's accessibility. The paper finds that micromobility service can shorten the travel time for potential public transit trips, especially in the first mile. Accessibility increments – the merit of micromobility services – are highly concentrated in the city center around the clusters of scooters and bus stops. The contribution of accessibility increment is also highly unequal, and small areas contributed most of the accessibility increments. The first-mile accessibility increments rapidly decrease and last-mile increment slightly increase with lower travel budget on scooters. Capacity simulations show that a group of users' accessibility increment will rapidly decrease with bigger group size. In conclusion, despite great potential in increasing public transit accessibility, dockless micromobility services still face major challenges of uneven distribution, high monetary cost, and low capacity, which warrants further attention from vendors and policymakers.

Declaration of interest

None.

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CRediT authorship contribution statement

Luyu Liu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Harvey J. Miller:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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