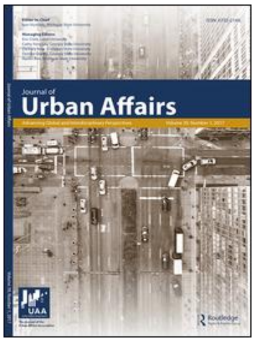

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From shared micro-mobility to shared responsibility: Using crowdsourcing to understand dockless vehicle violations in Austin, Texas

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From shared micro-mobility to shared responsibility: Using crowdsourcing to understand dockless vehicle violations in Austin, Texas

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ABSTRACT

In recent years, many progressive U.S. cities have witnessed the rapid popularization of dockless small vehicles as a car-free travel alternative to meet the short distance travel demand. The research gap exists in revealing the social outcome of the massive influx of shared small vehicles on public space. To that end, this study analyzed 4,100 parking violation reports in Austin, Texas, crowdsourced from the Austin 311 non-emergency service request system. The results showed that sidewalk and other public space intrusions were the two most frequently reported violations. Additionally, it found that improperly parked vehicles in parks required the longest time to be cleaned. Among the three reporting methods included in this study, 91% were submitted through smartphone applications, compared to 5% by phone calls and 2% through the web interface. The response time of smartphone reports was significantly greater than that of phone call reports (17.4 hours vs. 2.5 hours). Finally, the GIS hotspot analysis showed that university campus and downtown were both violation clusters, yet campus violations were solved more quickly. This study proposed a shared responsibility framework of key players in shared micro-mobility management and suggested using crowdsourcing 311 system data to facilitate communications between stakeholders.

Introduction

Shared micro-mobility is an innovative transportation strategy in the mobility-as-a-service industry. It provides users temporary access to low speed, usually single-occupancy, and small modes to satisfy their short travel demands (Shaheen & Cohen, 2019; Zarif et al., 2019). Since early 2015, dockless bike-share programs promoted by private companies such as Ofo and Mobike flourished rapidly in almost every big and small city in China (Mead, 2017). However, the glamorous situation did not last long. Improper use, such as illegal riding and parking, has inflicted severe damage to the dockless bike-share market in China (Yin et al., 2019). Feverish business rivalry and over-expansion without sufficient oversight have made the public space filled with abandoned, nonfunctional shared bikes. The market experienced a rapid shrink like its emergence as major bike-sharing services, Ofo and Mobike, announce bankruptcy or acquisition by another internet company (Reuters, 2018). Nevertheless, the success of shared micro-mobility at an early stage has generated a transportation revolution in short travels.

Similar to China, many progressive U.S. cities have also been proactively investing both human and capital resources in active transportation travel modes to reduce automobile trips (Graham-Rowe et al., 2011). Grappling the zeitgeist of the sharing economy and the prevalence of dockless technology, private vendors such as Lime and Bird succeeded in pioneering shared dockless electric scooters (e-scooters) programs in many U.S. cities (NACTO, 2019). Records showed that the Lime

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e-scooter program reached 6 million total ridership after 14 months since their release of dockless e-scooters. In addition, 30% of e-scooter riders reported the replacement of car trips with e-scooters (Ajao, 2019).

Although the domestic market has not yet mirrored the rapid rise and fall in China, we are beginning to witness similar disadvantages of indulgent development as the negative outcomes of overcrowded dockless vehicles in cities emerged gradually. Figure 1 shows some pictures we took in city parks (Figure 1(a,b)) and on streets (Figure 1(c,d)) in Austin. There was also evidence showing that sharing space with e-scooters could induce unsafe and agitating feelings for passersby (James et al., 2019). The reality presents a worrying circumstance where the dockless technology not only liberates us from the geographical constraints of bike stations but also diverts us from keeping our living space tidy and clear.

Challenges remain to urban planners as in how to establish an efficient response mechanism to manage the collateral damage to the public space. A potential solution is to proactively engage in the

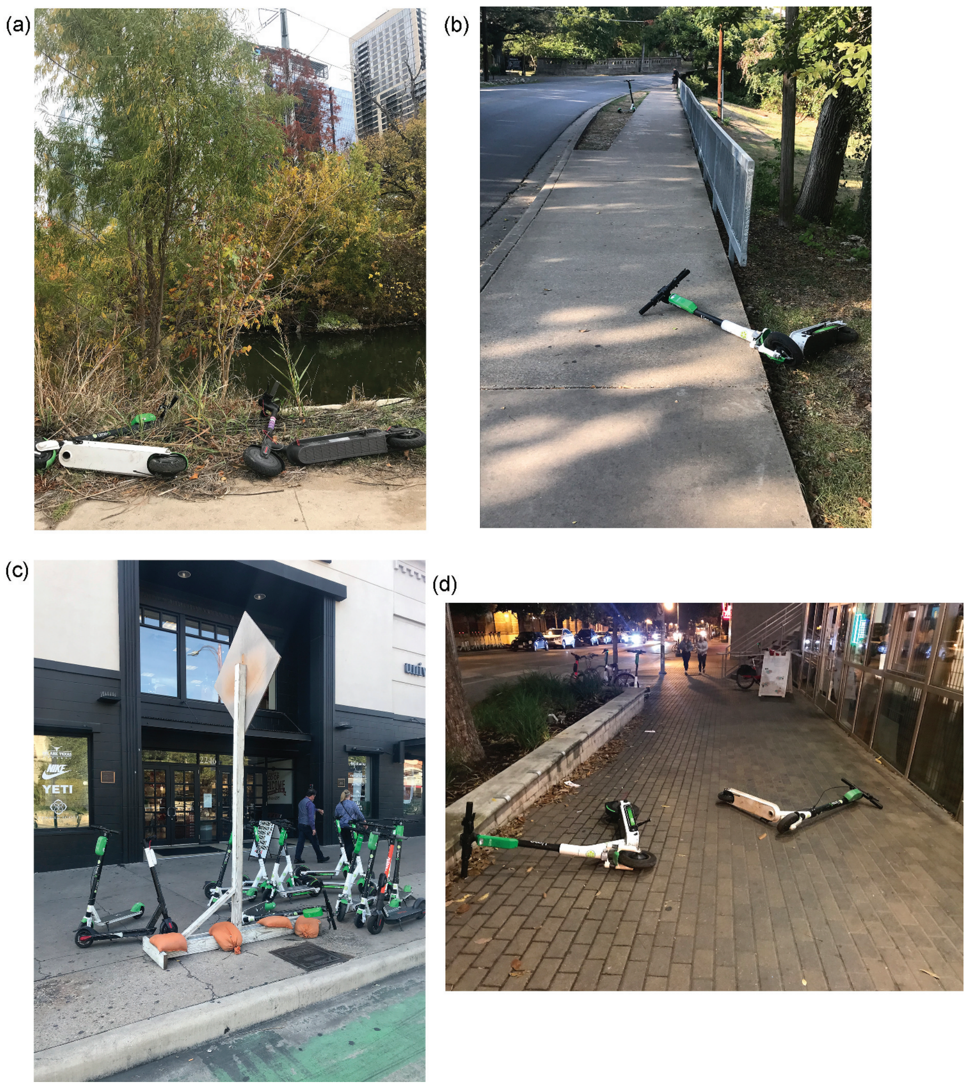

Figure 1. Abandoned e-scooters in parks and on streets blocking sidewalks and traffic signs near the downtown and campus areas in Austin, Texas.

local knowledge, namely the useful information provided by people outside the planning profession about these violations (Hanna, 2000; Özdemir & Tasan-Kok, 2019; Van Herzele, 2004). On that note, this paper aimed to answer the following research questions by using crowdsourced dockless e-scooter violations reported by the 311 non-emergency service channel in Austin, Texas: (1) What were the dockless mobility violations in Austin and what were possible reasons which cause longer response times? (2) Where did the violations cluster? Answers to these questions will provide direct suggestions to Austin local micro-mobility planning practice and showcase the power of crowdsourcing data in facilitating planning processes in the shared responsibility framework.

Literature review

The notion of involving the general public in the decision-making process as a democratic approach to practicing urban planning originated from advocacy planning theory (Davidoff, 1965; Forester, 1994) in the 1960s. Since then, participatory planning has evolved into several subsequent planning theories so that it was considered at the core of 21st-century planning practice at different scales (Fainstein, 2000).

In the recent decade, with the advancement of internet and smartphone technology, the power of social media in co-producing knowledge for urban planning practice has brought new insights into the participatory planning process (PPP) design (Brabham, 2012). Crowdsourcing usually refers to a bottom-up data collection approach by which authorities obtain information and knowledge from and with grassroots communities through online applications (Brabham, 2008; Smith, 2015). The approach resonates with the epistemological standpoint of public participatory planning theory by acknowledging the validity of innovative solutions provided by community members to the problems that perplex experts (Brabham et al., 2014; Radil & Jiao, 2016). Besides conceptualizing crowdsourcing in the framework of participatory planning, a rich empirical research body in the scholarship also has demonstrated the promise of active transportation planning in practice with the crowd based on user-generated datasets (Griffin & Jiao, 2015, 2019b).

The central research questions of previous behavioral studies in this domain were often related to the spatiotemporal usage patterns of (dockless) bikes or scooters, typically through illustrations on the ridership within the study area (Griffin & Jiao, 2015, 2019a). Based on the crowdsourced trip records with temporal information and geo-tagged origin-destination (OD) information, scholars have used GIS visualization (Jestico et al., 2016; Musakwa & Selala, 2016) and traffic assignment modeling (McArthur & Hong, 2019) in the transportation demand management field (McNally, 2000) to discover the spatial layout and patterns of travel behaviors. In order to understand how micro-mobility trips are related to surrounding built environments, researchers also used regression and statistical modeling to answer a deeper question of how to predict or shift user behaviors based on the connections as a way to guide planning practice (Bai & Jiao, 2020; Jiao & Bai, 2020).

Another type of research aimed to co-produce planning knowledge using crowdsourcing as a method to collect public opinions. For example, by analyzing public inputs on bicycling and walking in Austin, Texas, from different communication channels, Griffin and Jiao compared the traditional in-person meetings with public participatory geographic information systems (PPGIS) and the smartphone platform for participation. They concluded that crowdsourcing, as a data collection approach, increased the inclusiveness of PPP from the perspectives of both geography and equity (Griffin & Jiao, 2019a). In another study, Griffin and Jiao showcased the advantages of crowdsourcing as a handy tool to collect local knowledge from a stakeholder's standpoint by analyzing the suggested bike-share stations on PPGIS platforms with the built ones (Griffin & Jiao, 2019b). By mining posts on social media via emergent textual analytics in machine learning, researchers have found both positive public perceptions of dockless mobility operations (Rahim Taleqani et al., 2019) and safety concerns by synthesizing public opinions obtained from social media platforms such as Twitter or Instagram (Allem & Majmundar, 2019).

Our study complemented the current body of literature by making contributions to the following aspects. In contrast to social media platforms, we directly analyzed the violation reports from those whose lives were interrupted by micro-mobility operations. In this way, we can expose more issues in these operations, which were otherwise hidden by promotional advertisements and mixed comments on social media. Since the 311 non-emergency service request system is a governance-oriented, structured participatory process that is not only open but also controllable, mining the public opinion there could generate more concentrated information about management strategies (Brabham et al., 2014). On that note, this study explored how much information the current system could provide to help the city government consolidate the information exchange processes in a shared responsibility framework.

Methodology

Study area and data

As one of the major technology hubs in the United States, Austin has a long history of accommodating various shared micro-mobility modes, such as docked or dockless bike-sharing, and e-scooters. As of 2019, there are seven listed licensees currently operating over 15,000 dockless vehicles in operational zones authorized by the local government. Since the launch of the scooter-share program in March 2018, over 1.7 million total vehicle trips were generated, with approximately 1.4 million vehicle miles traveled in less than one year (Jiao & Bai, 2020). To respond to the dramatic influx, Austin has announced strict rules for vehicle deployment and operation, including the service area, right-of-way, device specifics, parking, and violation management mechanisms among other principles for licensees (Austin, 2018).

This study focused on dockless vehicle violations reported by the public to the city of Austin through 311 service request platform. To facilitate public participation in dealing with misbehaviors of dockless mobility, Austin city government encouraged citizens to report the issue via the 311 system when seeing e-scooter misconducts. The 311 system is a hotline system launched by the city government in Baltimore, Maryland, back in the 1990s. The founders there aimed to increase public involvement in municipal affairs by encouraging people to call and report. Now, it has evolved with the advancement of smartphone and internet technology so that citizens can get involved either by phone calls, web interface, or smartphone applications.

Although the 311 data has both advantages and disadvantages in studying public participation in administrative affairs, it is undoubtedly a sound, rich data source for urban policymakers and researchers to engage the public voice (Lerman & Weaver, 2014; Levine & Gershenson, 2014; O'Brien et al., 2015; White & Trump, 2018). From April to September of 2019, we web-scraped 4,191 reports regarding shared micro-mobility (bikes and e-scooters) violations from the Austin 311 report system. The information included in the crowdsourced dataset is provided in Table 1. After data cleaning, there were 4,100 completed reports included in the data analysis.

Kruskal-Wallis analysis of variance (ANOVA) test

Analysis of Variance (ANOVA) is a statistical approach to examine the difference of averages among different groups. Many transportation researchers use the technique to test the hypothesis of whether a statistically significant difference exists, such as social exclusion in various urban transport systems (Özkazanç & Özdemir Sönmez, 2017) or travel behaviors in different land use-transportation systems (McNally & Kulkarni, 1997). In our study, we focused on groups with varying submission times, violation types, companies involved, and reporting methods, respectively.

There are four assumptions in a one-way ANOVA to consider: normality, homogeneity of variance, equal sample size, and independence of groups (Brereton, 2019). The last assumption was easy to confirm in that all groups in each category were mutually exclusive. Besides, variances

Table 1. Summary of 311 shared micro-mobility violation reports.

Category	Name	Description
Key identifier		
	Report ID	A unique identifier of a specific report.
Temporal information		
	Submission time	The time a citizen submitted a report.
	Case open time	The time a report was opened as a case to be solved.
	Case close time	The time a case was closed by the involved licensee or the city.
Spatial information		
	Address	The closest street address where the violation was witnessed.
	latitude/ longitude	The exact geographic coordinates for the witnessed violation.
Report content		
	Name	An automatically generated name for the report.
	Status	A flag indicating whether the report was dealt with.
	Description	The self-reported description of the violation.
	Violation type	Self-reported violation type based on location and issue.
	Company name	The self-reported company name that the citizen recognized by the appearance of the vehicle.
	Vehicle color	Self-reported vehicle color of the misbehaved vehicle.
	Issue regarding	Self-reported vehicle type, including bikes and scooters.
	Reporting method	The channel a citizen used to report a violation, including phone calls, smartphone app, and web interface.

Table 2. Violation response time by report time of day on weekday/weekend.

		Response time (hours)			
Submitted time	# Violation	Min	Median	Max	Mean
Morning, weekday	1416(34%)	0.1	3.2	846.8	43.8
Morning, weekend	430(10%)	1.5	46.9	533.9	57.8
Afternoon, weekday	781(19%)	0.2	17.0	935.3	52.9
Afternoon, weekend	389(9%)	0.2	42.2	887.2	65.0
Evening, weekday	547(13%)	0.2	14.9	834.8	46.8
Evening, weekend	229(5%)	0.2	38.1	1240.0	60.2
Night, weekday	205(5%)	0.2	12.0	806.9	52.2
Night, weekend	103(2%)	2.0	36.0	540.8	68.4
Total	4100(100%)	0.1	17.0	1240.0	51.4

were found among different groups in each category. Thus, the homogeneity of variance assumption was met. However, through Tables 2 to 5, we observed various sample sizes in each group. As a result, the one-way ANOVA was invalid in this case.

Therefore, we applied a non-parametric method equivalent to one-way ANOVA named Kruskal-Wallis ANOVA to avoid the possible type I error (Feir-Walsh & Toothaker, 1974). Kruskal-Wallis test releases the constraints on the normal distribution and identical group size by comparing the median (ranked mean) of a group with each other rather than the grand average (Hecke, 2012; Ruxton & Beauchamp, 2008; Vargha & Delaney, 1998). In our case, with a 0.05 significance level, the null hypothesis was that different groups would have the same median response time. This analysis answered the first research question of possible triggers for management delays.

To simplify the comparison, we reduced the number of groups for the analysis. First, we combined hours of the day into morning hours (6:00–12:00), afternoon hours (12:00–17:00), evening hours (17:00–20:00), and night hours (20:00–6:00). We also separated weekdays from weekends under the assumption that a report could take longer to deal with if it was submitted on weekends. Finally, we generated eight response time groups by creating interaction terms between four subcategories based on hours of the day

Table 3. Violation response time by violation type.

Violation type	# Violation	Response time (hours)			
		Min	Median	Max	Mean
Sidewalk obstruction	1705(41%)	0.1	15.4	865.3	50.9
Obstruction (parking lot, public property, etc.)	1472(35%)	0.1	17.0	1240.0	49.8
Damaged device	405(9%)	0.1	19.6	935.3	58.1
Device on private property	303(7%)	0.2	15.3	790.4	49.4
Device in parks	215(5%)	0.3	35.9	309.8	56.1
Total	4100(100%)	0.1	17.0	1240.0	51.4

Table 4. Violation response time by the affiliated company.

Affiliated company	# Registered dockless vehicles on the city website	# Violation	Response time (in hours)			
			Min	Median	Max	Mean
Bird	4,500 scooters	1213(29%)	0.1	15.8	887.2	35.2
Jump	2,500 scooters+2,000 e-bikes	764(18%)	0.1	10.6	858.7	31.5
Lime	5,000 scooters	1148(28%)	0.1	28.0	935.3	79.4
Lyft	2,000 scooters	628(15%)	0.1	16.3	887.1	36.6
Ojo	1,000 scooters	38(0%)	0.6	23.2	266.8	56.3
Razor	Not shown	4(0%)	115.8	555.8	797.5	506.3
Skip	Not shown	74(1%)	3.5	157.0	1240.0	244.9
Spin	750 scooters	139(3%)	0.3	15.5	449.8	34.4
Veoride	Not shown	84(2%)	0.3	13.6	293.5	21.2
Windmobility	Not shown	4(0%)	0.5	57.5	790.4	226.5
Multiple Companies	-	4(0%)	0.2	0.3	1.5	0.6
Total	>17,750	4100(100%)	0.1	17.0	1240.0	51.4

Table 5. Violation response time by reporting method.

Reporting method	# Violation	Response time (in hours)			
		Min	Median	Max	Mean
Phone call	238(5%)	0.2	2.5	797.5	30.9
Smartphone app	3759(91%)	0.1	17.4	1240.0	52.4
Web interface	103(2%)	0.1	18.7	865.3	60.5
Total	4100(100%)	0.1	17.0	1240.0	51.4

and two based on the day of the week (Table 2). All groups in other variables of interest were preserved for reaching as many conclusions as possible (Table 3–5).

Geospatial analysis

To identify the clustering effect of response timeliness, we conducted a hotspot analysis using ArcGIS software. A hotspot analysis in GIS uses Local Moran's I index to test whether the geographical distribution of a phenomenon is clustered (Anselin, 2010). An extensive literature of case studies has utilized the method to study the clustering effect in transportation such as low-carbon travel blocks (Hou et al., 2019) and bike-sharing stations (Griffin & Jiao, 2019b). The hotspot analysis workflow in this study was the following. First, we conducted a spatial auto-correlation test on the response time at the 0.05 significance level. We confirmed a statistically significant spatial autocorrelation of response timeliness in different parts of Austin, meaning there could be some clusters with a relatively lower response time and others with a longer response time. Then, based on the hotspot analysis, we further categorized violation locations into three classes: insignificant points, statically significant clusters of high or low values, and outliers.

Results and conclusions

E-scooter violations in Austin, Texas

As is shown in Table 6 below, all differences in median response time were statistically significant.

Submission time

First, most violation reports were submitted on weekday mornings and also were responded to most rapidly. It is easy to understand as staff were most likely to be working in the morning hours (Blake, 1967; Goldstein et al., 2007). Further, there were significantly fewer reports submitted at nights after working hours. Thus, there were not many leftover cases to be fixed the following morning. Although citizens could report a violation on a weekday afternoon, it was very likely that the case was delayed due to overwhelming morning cases. Alternatively, an afternoon report could not be responded to until the next morning if it was submitted after working hours. In this case, afternoon reports had to wait longer times than weekday night violations. Interestingly, on weekends, morning reports had the longest response time, and the night reports had the shortest on average. The response time pattern on weekends made sense in that fewer employees would work on weekends. Thus, weekend reports were put aside until Monday.

Table 6. Kruskal-Wallis test results on median response time (hours) in different groups.

Category	Groups	# observation	Median	d.o.f	Chi-squared	p-value
Period of day	Morning	1846	5.47	3	95.44	0.0001
	Afternoon	1170	19.70			
	Evening	776	15.46			
	Night	308	15.54			
Day of week	Weekday	2949	11.72	1	416.30	0.0001
	Weekend	1151	41.07			
Period of the day by day of week	Weekday morning	1416	3.22	7	553.63	0.0001
	Weekend morning	430	46.94			
	Weekday afternoon	781	17.00			
	Weekend afternoon	389	42.20			
	Weekday evening	547	14.88			
	Weekend evening	229	38.08			
	Weekday night	205	12.00			
	Weekend night	103	36.00			
Violation type	Device on private property	303	15.28	4	30.10	0.0001
	Device in parks	215	35.93			
	Sidewalk obstruction	1705	15.43			
	Damaged device	405	19.63			
	Obstruction (parking lot, public property, etc.)	1472	16.99			
Company	Bird	1213	15.75	10	357.76	0.0001
	Jump	764	10.59			
	Lime	1148	28.03			
	Lyft	628	16.33			
	Multiple	4	0.29			
	Ojo	38	23.22			
	Razor	4	502.91			
	Skip	74	156.89			
	Spin	139	15.47			
	Veoride	84	13.57			
	Windmobility	4	9.46			
Reporting method	Phone call	238	2.54	2	88.27	0.0001
	Smartphone app	3759	17.42			
	Web interface	103	18.68			

Violation type

The dataset showed that improperly placed dockless vehicles on sidewalks (41%) and other public spaces (35%) were two common violations. Nevertheless, the handling time of these two frequently reported issues was moderately low (15.4 and 17.0 hours, respectively). Surprisingly, although fewer park-related reports were submitted, the response time of park violation was much greater than that of others (35.9 hours). Admittedly, public spaces like sidewalks and parking lots were much more frequently used by a larger population than parks, so dockless vehicles invading these areas were reported more often. As a result, the city and private companies would typically pay more attention to more problematic issues and react faster. Moreover, public spaces like sidewalks and parking lots parks were more open and accessible. Hence, the licensees could also easily approach these areas to fix the problems. They were able to handle the reports when redistributing or collecting vehicles in the neighborhood with no extra effort. However, since they were forbidden to deploy vehicles in parks, violations in parks would naturally require more human power and time.

Reporting method

The reporting method visualization was the most interesting case that we encountered during the analysis. We saw that people overwhelmingly preferred to submit violation reports through smartphone applications (91%). Albeit making phone calls was less commonly used, it was the most efficient way to have violations handled (2.5 hours). The result showed that information sharing efficiency in handling dockless vehicle violations between the licensees and the 311 system was largely affected by the reporting method.

The observation was easy to understand. For one, it is normal in our daily life that the most efficient way to communicate is through conversations. Compared to smartphone applications and web interfaces, which are one-time information feeding processes, having a conversation with a specialized operator was a bi-directional, back-and-forth information exchange process. Using this channel, city officials can stimulate more knowledge co-production in interactive communication to facilitate the future response process. Comparably, the city had less control in information acquisition, losing detailed guidance on how to pass along the local knowledge in a short, online report to the response team. In addition, a second reason alluded to the fact that online reports can accumulate to a considerably large amount before being distributed to responsible parties. The mismatch between large amounts of public participation through online platforms and the much longer response time was proved to be a challenge during information exchange between stakeholders in micro-mobility management.

How the location of a violation affected the response time?

As of now, we have discussed possible reasons that caused delayed responses to violations. Further, in GIS hotspot analysis, we answered the second question by visualizing the geographic clusters (Figure 2). Table 7 below summarized the basic descriptive statistic scores of each type of cluster. We can see that over 80% of violation reports did not show a statistically significant clustering effect, meaning the violations with different response times only concentrated in a small proportion of the study area. In the clustered area, HH clusters denoted that a violation report with longer response time was also surrounded by violation reports with similar longer response times (i.e. violations geographically clustering with similar response times). Likewise, LL clusters showed that violation reports with shorter response times surrounded a violation report with a similar response time. Noticeably, there were also two outlier clusters. The HL and LH outlier clusters were areas where violations with higher response times existed, but all the neighbor violations had statistically significantly lower and higher response times, respectively.

Our GIS spatial analysis detected two clusters with different response time layouts (Figure 2). On the university campus, most violation reports were handled within a few hours (light blue dots). However, there was also a cluster of long response time reports concentrated at the center (red dots).

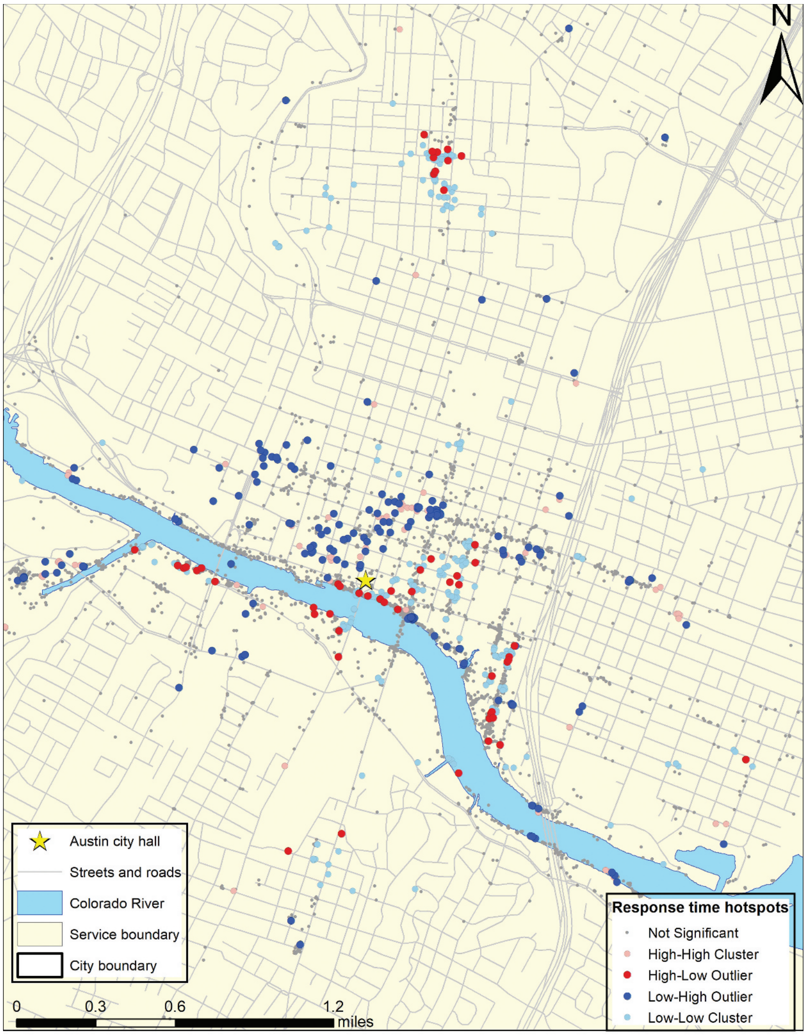

Figure 2. Zoomed-in shared micro-mobility violation hotspots by response time.

Table 7. Basic descriptive statistic scores of violation report clusters by response time (hours).

Cluster	# Violation	% Violation	Min	Median	Max	Mean
HH	84	2%	51.47	189.81	865.28	51.37
HL	58	1%	51.35	115.31	886.68	10.90
Insignificant	3457	84%	0.12	17.27	1240.00	206.96
LH	185	5%	0.17	6.93	50.65	165.71
LL	316	8%	0.15	3.54	50.55	13.97

Spatial auto-correlation was tested at the significance level α = 0.05.

Besides, although there were significantly more violations in the downtown Austin area, most of them were handled within relatively shorter times than others nearby (dark blue dots). Unlike the campus, we identified a clear belt of long response time violations alongside the Colorado River banks (red dots) where people can walk or bike on trails and parklands. The visualization conformed to the result in the ANOVA analysis.

Discussion

In a Shakespearian tragedy, we always see a tragic hero born with a fatal flaw, struggling between good and evil. "To be or not to be dockless" is a Shakespearian question for shared micro-mobility (Gu et al., 2019). The dockless system is the tragic hero currently struggling between the virtue of flexible, car-free travel experience and the disvalue of overcrowded vehicles engulfing the public space in our cities. The overgrowth of dockless transportation systems in many Chinese cases has alerted us of a tragic ending if we do not strive to control the damage to our society promptly (Tu et al., 2019; Yin et al., 2019).

The promises of applying big data methods like crowdsourcing as a way to facilitate public participation in shared micro-mobility management are as inspiring as the supernatural element in a Shakespeare play. However, it is a challenging task for transportation planners. Like any other empirical practice on big data, a major challenge is that messy, informal inputs in the knowledge co-production process constantly affect the accuracy of responses and the efficiency of producing them (Chen et al., 2016). In this study, for instance, due to the lack of follow-up function in the report system, we had to assume a violation was as the reporter described and it was resolved before closing. We could not retrieve more information about a closed case, such as who resolved the issue by doing what and when. Moreover, it also lacked a function to allow reporters to comment on whether the result was satisfactory, or the violation remained uncared even though the status showed that the case was closed. It was hard for us to confirm whether a case was truly resolved and how the result was. The limitation of less detailed and accurate information could hamper the operation efficiency and require more iterative adjustments in practice.

Regardless, we have demonstrated a handful of merits of incorporating big data techniques in urban affairs from this study. Crowdsourcing public opinions from platforms like the 311 service request system can aggregate piecemeal local knowledge and transform them into valuable guidance in planning practice. For instance, in this study, we identified issues such as inefficiency in dealing with online reports and park-related violations near the riverbank. Evident findings like these from crowdsourcing could guide micro-mobility agencies to redistribute their resources to better respond to the most urgent issues in the future.

Finally, we proposed a framework of shared responsibility triangle between the public, city government, and private licensees (Figure 3). Crowdsourcing public opinions from the 311 system can contribute to each arrow in the framework. First, it can gather much more feedback through a bottom-up approach in a relatively short amount of time, making the knowledge generation process more promptly as soon as the drawbacks emerge (Bott & Young, 2012). Then, based on the results from the analyses like we conducted in this study, city staff could identify predominant issues and adjust license regulations to alleviate the impacts on society. Finally, the licensees could change their user instructions to address misbehaviors and enact restrictions or penalties on

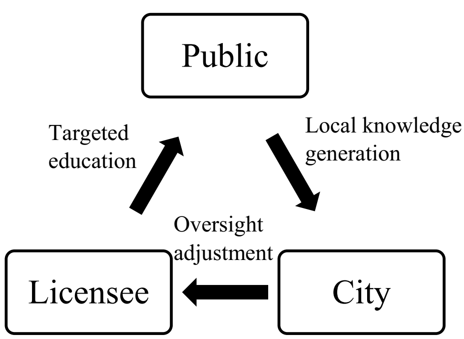

Figure 3. Roles of crowdsourcing public opinions in the shared responsibility.

improper use according to the regulations from the city. The shared responsibility framework is an iterative loop as long as the platform is well maintained and the city staff is responsive. The framework from this case study in Austin was successful in feeding rich and timely information to city staff about the disadvantages of micro-mobility programs. The framework applies to cities that have already had booming micro-mobility markets and those eager to embrace the business but are hesitant about the collateral damage to their public space. Furthermore, the current framework in Austin only allows one-time participation for the lack of follow-up mechanisms. In the future, cities should consider complementing a function in their platform architecture that enables response teams and reporters to comment on a closed case.

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