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Assessing the Impacts of Air Quality Alerts on Micromobility Transportation Usage Behaviors

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A R T I C L E I N F O

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A B S T R A C T

To address the severe risks imposed by air pollution, governments around the world have prioritized air quality information disclosure and alert dissemination with a goal to evoke awareness and ultimately encourage behavior changes. Daily transportation behavior not only contributes to air pollution formation but also impacts personal exposure. Previous studies have identified mixed results about the effectiveness of air quality alerts in encouraging transportation behavioral changes. However, little is known about the impacts on micromobility usage, a newly introduced transportation mode, which directly exposes the riders to the ambient environment and usually takes place in heavy traffic areas. In this study, we conducted a case study in Austin, TX, analyzing over 6.9 million trips collected between April 2018 and September 2019. A Poisson multivariate regression model was applied to assess the relationship between air quality alerts and usage of micromobility vehicles. The results indicate that air quality alerts in the form of Ozone Action Days do not alter micromobility usage behavior, while the public does significantly change their usage behaviors in response to actual ambient air quality for short duration trips. Numbers of longer distance micromobility trips were not found to be sensitive to actual air quality. The findings of this study have important implications for policymakers: government agencies should carefully consider timing, accuracy, and message clarity when delivering air quality information to the public.

1. Introduction

Air pollution is a longstanding and troublesome issue facing government agencies around the world due to its severe impacts on both public health and well-being, and economic growth. However, after decades of efforts, the “State of the Air 2021” report still found that nearly 135 million people, or over 40% of the population, in the U.S. were still living in areas with unhealthy air quality levels, which put them at risk of excessive morbidity and mortality (American Lung Association, 2021). The widely acknowledged association between air pollution and occurrences of respiratory and cardiovascular disease (Hoek et al., 2013; B.-J. Lee et al., 2014), and even susceptibility to infectious disease such as COVID-19 (Wu et al., 2020; Xu et al., 2022), demands that global governments prioritize policies to address air pollution.

The success of such air pollution policies rely heavily on not only technical solutions like monitoring, modeling, and predicting the air quality, but also public behavioral responses (Petts, 2005). Public engagement is a key to addressing this problem. It was found that active public participation in the decision making process of alleviating air pollution could effectively improve air quality (Leng, Zhong, & Kang, 2022). However, though the general public is aware of high concentrations of air pollutants in certain areas, they are often oblivious of the extent to which they are exposed to air pollution in their surroundings (Delmas & Kohli, 2020). One of the obstacles in increasing people’s awareness of ambient air quality is that it is usually neither visible nor perceptible to the public, and people’s perceptions of air quality may be wrong (Kim et al., 2019; Schmitz et al., 2018). Thus, efforts have been made to enact air quality information communication policies to make local air quality information more accessible to the public with a goal of persuading behavioral changes towards more healthy and sustainable ones (Ahmed et al., 2020; Bickerstaff, 2004). Many metropolitan areas in the U.S., for example, engage in air pollution action days by sending out air quality alerts when the concentration of certain pollutants on the following day is predicted to exceed the pre-defined limits. The air quality alerts not only deliver information about the health impacts of air pollution but also encourage environmentally friendly behaviors to reduce air pollution formation, since public participation in collective

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actions has been proposed as a promising direction for environmental policy (Lubell et al., 2006). Air quality alerts are usually disseminated through local news, government websites, social media, and opt-in emails. Evaluating the effectiveness of air quality information communication approaches in persuading behavioral changes is critical for informing decisions relating to such policies.

Our daily transportation behavior is a major contributor to air pollution formation and the corresponding risks of exposure. First, transportation emissions have long been recognized as a major contributor to overall air pollution and the pollutants in vehicle exhaust are closely associated with increasing morbidity (Pinto et al., 2020; Samoli et al., 2016). It was estimated that nearly 385 thousand deaths and $1 trillion in health damages were associated with tailpipe emission induced air pollution in 2015 (Anenberg et al., 2019). Second, a large part of our daily air pollution exposure results from our transportation behaviors, which is especially true in vehicle-intensive metropolitan areas and locations with high proximity to traffic (Karanasiou et al., 2014; Knibbs et al., 2011; Zuurbier et al., 2010). Time spent in transportation accounts for about 21% of personal exposure and 30% of inhaled black carbon (Dons et al., 2012). Therefore, it is necessary to reduce air pollution exposure during transport-related activities.

Due to the critical role played by transportation activities, researchers have examined the responses of transportation behaviors to air quality alerts. In previous studies on driving behaviors, Henry and Gordon (2003) found a significant decrease in miles driven by government employees but no impact on daily driving trips and miles driven by other groups in Atlanta on air quality alert days. Cutter and Neidell (2009) found a significant reduction in daily traffic volume in the San Francisco Bay area but none on daily public transit use in response to air quality alerts. Another study in Salt Lake City, Utah, also investigated changes in traffic volume in response to air quality alerts but found no significant changes, but did observe decreases in the downtown area and increases in the outlying mountain areas (Tribby et al., 2013). Noonan (2014) investigated the driving behavioral responses to air quality alerts in over 300 cities across the U.S. and found only weak evidence to support a finding of a decrease in driving time.

In contrast to the pessimistic results on response from driving behaviors, recent studies on cycling behaviors present promising findings that cyclists might change their behaviors in response to air quality information. For example, air quality alerts significantly reduced the number of daily cycling trips in Sydney, Australia (Saberian et al., 2017). Morton (2020) also examined the association between cycling behavior and air quality in London finding that increased ozone level was linked with lower levels of cycling demand, while higher PM_{10} concentration was associated with more cycling trips. Another study in Beijing, China also showed that hazy weather could significantly change cycling behaviors (Zhao et al., 2018). Compared to driving, cycling directly exposes the riders to the ambient environment and the physical demand of pedaling increases the amount of air inhaled, which may explain the observed significant association between cycling behaviors and poor air quality information.

With increasing urbanization, shared micromobility is becoming a popular solution to congestion, emission issues, and first/last mile problems (Baltimore City Department of Transportation, 2019). Similar to cycling, though without the need to pedal, riding on a micromobility vehicle exposes the rider to surrounding air pollution. In addition, micromobility trips usually happen in heavy-traffic areas like city centers, which puts the riders at higher risks of air pollution exposure. Through over 2000 person-days of human subject monitoring, Dons et al. (2019) found participants were most likely to encounter peak exposure to air pollution while in transportation, which was especially evident when on bikes. It has been suggested that the health benefits from restricting active commuting like walking and cycling during high pollution days does not detract from physical activity in the long term (Giallouros et al., 2020). Unlike cycling, riding on a micromobility vehicle may not benefit the rider's health due to limited demand of physical activities. At the same time, it is worth noting that people who engage in such active transport bear the disproportional burden of increasing exposure to air pollution, especially during high pollution days (Gelb & Apparicio, 2021). Because of the vast popularity of micromobility vehicles and their unique characteristics, understanding the impacts of air quality alerts on micromobility behaviors can help to evaluate the impacts of micromobility on public health and environmental sustainability and inform better decision making for policymakers. Yet, studies on this relatively recently emerged transportation mode are limited. To address this research gap, the objective of this study is to assess the effectiveness of air quality alerts in influencing micromobility behavior. In doing so, this work explores implications for policymakers in information policy design by examining how the public responds to air quality information and how policies can be improved to better engage the public in behavioral changes. Overall, this study aims to answer the following research question:

How do people change their micromobility usage behavior in response to air quality alerts?

2. Methodology

2.1. Data collection

This study incorporated micromobility usage data, air quality data, and a series of other possible confounding parameters in the research setting of Austin, TX, to investigate behavioral responses on micromobility vehicles to air quality alerts. The emergence of e-scooters and e-bikes offers an opportunity for researchers to investigate transportation behaviors through a rich collection of administrative data rather than self-reported data from surveys or interviews. Austin is one of the cities that mandates data disclosure from micromobility companies and ranks among the largest in terms of system size of shared micromobility in the U.S. In this study, micromobility data on shared dockless scooters and e-bikes was collected for analysis.

The data was provided by the City of Austin Transportation Department through the official open data portal (City of Austin Transportation Department, 2020). This dataset contains information on each micromobility vehicle trip made within the Austin area since April 2018 and is updated every day. Each record in the dataset includes the unique device ID, vehicle type (i.e., bicycle or scooter), trip duration, distance, start and end time, and start and end census tracts of each trip. Over 6.9 million trips on micromobility vehicles took place from April 2018 through September 2019. To avoid the impacts of geofencing policies enacted in September 2019, which restrict the usage of micromobility vehicles in certain areas of the city, the end date of our study period is set to September 2019. After obtaining the micromobility data, abnormal records, namely with trip duration time below 0 or above 24 hours, or trip distance outside the range of 0.1 to 500 miles as suggested by Austin Transportation Department, were removed. Next, the data was aggregated on a daily basis by summing the trip counts made each day across the whole Austin area. Outliers of extreme daily trip counts, which were affected by large citywide events or festivals, were excluded from further study.

Austin sends out an air quality alert when the predicted Ozone concentration on the next day exceeds the federal air quality standards, which is called an "Ozone Action Day" (OAD) in Austin. When an Ozone Action Day is issued, the government alerts citizens through mass media (e.g., email, news, and social media). Dates with an ozone alert were retrieved through the Austin municipal government website. To control for the possible confounding effects of actual air quality, monitored air quality data were obtained through the Air Quality Index (AQI) Daily Values Report from Environmental Protection Agency (U.S. Environmental Protection Agency, 2020). Overall AQI is calculated based on the concentration of five major pollutants regulated by the Clean Air Act: ground-level ozone, particle pollution, carbon monoxide, sulfur dioxide, and nitrogen dioxide. In the U.S., AQI ranges from 0 to 500 and is classified into six levels of health concerns, and each level is represented by a corresponding color with a goal to promote public awareness and comprehension. AQI categorization of health concerns and color-coding information (US Environmental Protection Agency, 2014) can be found inTable 1. Usually, when the AQI value is no more than 100, namely at Good or Moderate levels of health concerns, the air quality is regarded as satisfactory and the negative health impacts are deemed negligible.

Meteorological parameters, which are likely to be confounding variables because of their impact on both air quality and transportation behavior, were also collected during the same study period. Weather information was measured through a weather station at Austin-Bergstrom International Airport. Parameters including average temperature, maximum wind speed, relative humidity, and precipitation were selected in this study. The weather information was collected from Weather Underground (Weather Underground, 2021).

2.2. Statistical analysis

To estimate the micromobility behavior responses to air quality alerts, daily micromobility counts were examined through a multivariate Poisson regression. Since the goal of our study is to examine the effectiveness of air quality alerts, which is a form of information policy, we chose regression as our policy analysis method. The two main types of policy analysis methods are qualitative and quantitative. There are diverse methods in the quantitative field ranging from randomized controlled trials (RCT) and observational studies to regression models. Both RCT and observational studies require a counterfactual for causal inference through controlled experiment or quasi-experiment, which are usually expensive and time consuming. Regression is therefore a popular way in quantitative social science for policy analysis and has been widely adopted in previous studies (Saberian et al., 2017; Tribby et al., 2013; Zhao et al., 2018). By controlling for the impacts of possible confounding factors, regression models are able to enhance the validity of the study compared to simple (non)parametric tests or two-variable correlation. Based on the types of data collected, different regression models can be applied. With individual-level data, Zhao et al. (2018) were able to use a logistic regression model to analyze the impacts of demographic characteristics on cycling behavioral changes during polluted days. Yet, survey data is prone to bias from memory recall errors and social desirability, among other factors. In this study, we were able to collect population-level administrative data; thus, a multivariate regression is appropriate for the analysis with the capability of controlling for possible confounding factors. The regression model can be expressed as:

$$\begin{aligned} Log(micromobility\ behavior) = \beta_0 + \beta_1 \times OAD + \beta_2 \times AQI + \beta_3 \\ \times Day\ Type + \beta_4 \times interaction(AQI,\ OAD) \\ + \sum_i \beta_i \times Meteorological\ parameter(i) \\ + \phi_t + \varepsilon \end{aligned} \tag{1}$$

Where

β_0 intercept,

β_i $(i \neq 0)$ estimates for each independent variable,

OAD whether an alert is issued (1) or not (0),

AQI actual air quality level, acceptable (0) or AQI value beyond 100 (1),

Day Type day of week and holidays

Meteorological parameters temperature, precipitation, wind speed, relative humidity,

ϕ_t time-fixed effects

ε error term.

The dependent variable is the micromobility behavior in Austin: daily trip counts on micromobility vehicles. The focus independent variable is a dummy variable representing whether an alert (OAD) is issued or not. The model controls for the effects of actual air quality (AQI), meteorological parameters and day type (which is categorized into: Monday to Thursday, Friday, Saturday, Sunday, and federal or state holiday). In addition, interaction between the air quality alert and actual air quality was considered by adding an interaction term in the model to examine if the impact of one variable would depend on the other variable. In our model, the interaction term is the product of the two variables. Micromobility vehicles are a relatively recently introduced and increasingly popular mode of transportation in Austin. Therefore, the daily trip count increased substantially over much of the study period. A time parameter ϕ_t representing time-fixed effects was added into the regression model to account for this increase. A multicollinearity test was conducted using generalized variance inflation factor (GVIF) and the results are provided in the supplementary material.

To investigate the sensitivity of different types of trips, trips were further categorized based on distance traveled into two classes: short-distance and long-distance. Daily trip counts of the two types were fitted into the same model. In this study, trips were sorted by distance ascendingly and those ranked in the top 80% were labeled as short-distance trips with the remaining 20% categorized as long-distance trips, since the distance distribution is close to a Poisson distribution with a long tail as can be seen in Fig. 1. The resulting cutoff threshold of 1.5 miles was set in this manner since the information on the exact start and end point of each trip was not available and the trip purpose could not be inferred.

3. Results

3.1. Data Summary

Micromobility data from the first three months beginning April 2018 were removed due to existence of too many missing data points and a steep data ramping up period as micromobility systems were introduced to the area. Daily trip counts of micromobility vehicles over the remaining study period are plotted in Fig. 2, where the blue line indicates the data trend by a local regression technique LOESS (i.e., locally estimated scatterplot smoothing).

3.1.1. LOESS

LOESS is a locally weighted regression method (Cleveland, 1979) used for data visualization of the micromobility usage trend in our study. LOESS combines the simplicity of linear least square regression with the flexibility of nonlinear models by fitting low-degree polynomial models on subsets of the data. The span of the subset is determined by the smoothing parameter α. The weight of each point is determined by how close it is to the focal point and the nearest points get more weight. After getting the regression values for each point, LOESS is complete. A general upward trend over time for this new mode of transportation can be observed.

Next, the spatial distribution of the micromobility trips is explored and plotted in supplementary material Fig A.1 Eqn (1), indicating the number of trips made within each census tract in Austin. As the figure shows, most of the trips occurred in the center area of Austin, especially in the single central census tract in downtown, where over 2 million trips

Table 1
Air Quality Index (AQI) values categorization and corresponding levels of health concerns and colors.

Air Quality Index (AQI) values	Levels of Health Concerns	Colors
0 to 50	Good	Green
51 to 100	Moderate	Yellow
101 to 150	Unhealthy for Sensitive Groups	Orange
151 to 200	Unhealthy	Red
201 to 300	Very Unhealthy	Purple
301 to 500	Hazardous	Maroon

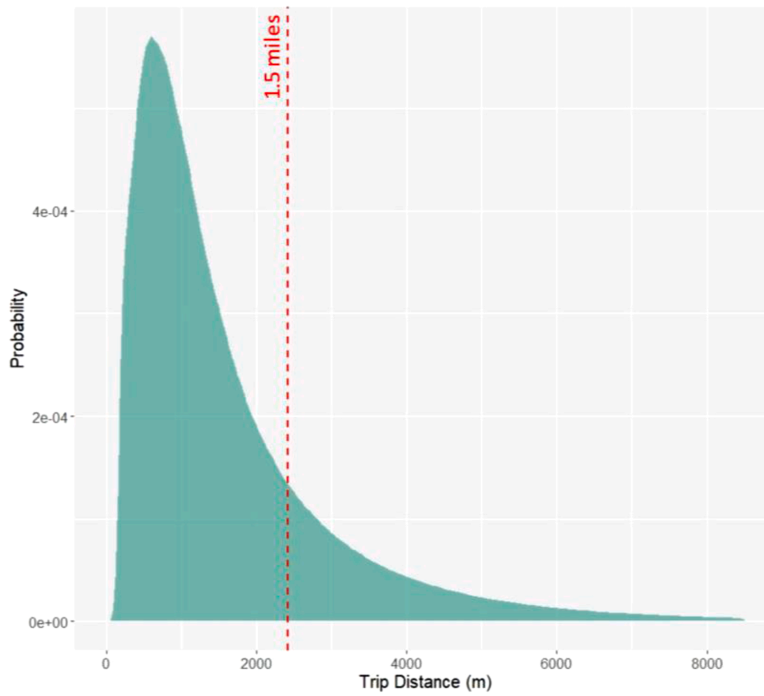

Fig. 1. Distribution of trip distance with a vertical dashed line representing the cutoff threshold at 1.5 miles.

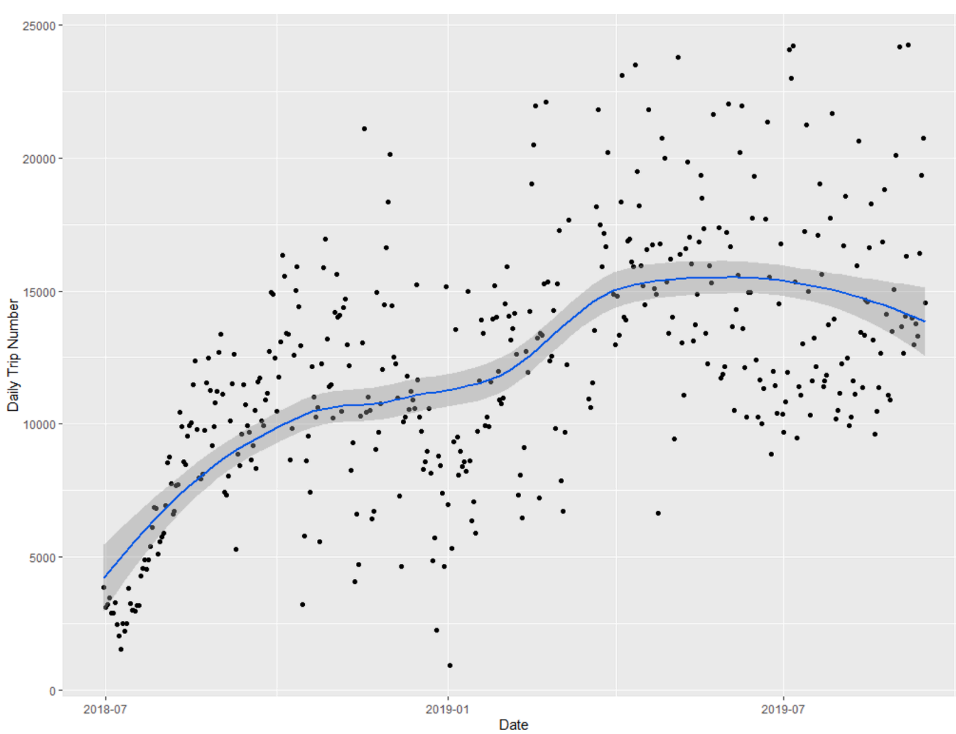

Fig. 2. Daily trip counts on micromobility vehicles over the study period with a local regression line indicating the data trend, and the grey band representing the 95% confidence interval.

took place during the study period.

During the study period, there were 10 days with unsatisfactory levels of actual air quality, namely an AQI index above 100, with major pollutants as either ozone or $PM_{2.5}$. For the air quality alerts, there were 10 Ozone Action Days issued, among which ozone concentrations of only three days on the days following the OAD alert day were beyond the federal limits, suggesting a prediction accuracy of around 30%. The distinction between actual air quality levels and predicted air quality levels and their varying impacts on micromobility usage behaviors is explored more in the following section.

3.2. Analytical results

Firstly, daily micromobility trip counts were fitted into the regression model shown in Eq. (1). Table 2 includes the results of the model. The "Variables" column represents the independent variables with the

Table 2
Results of daily micromobility trip counts

Variables		Estimate	Standard Error	t value	p value
Ozone Action Day (OAD)		2.19E-02	1.25E-01	1.75E-01	8.61E-01
AQI: Unhealthy for Sensitive Groups		-3.96E-01	1.25E-01	-3.15E+00	1.61E-03 *
Interaction(AQI, OAD)		1.93E-01	2.57E-01	7.50E-01	4.53E-01
Day type	Holiday	-5.25E-01	9.47E-02	-5.5E+00	3.00E-08 *
	Mon. to Thurs.	-2.79E-01	4.74E-02	-5.89E+00	3.93E-09 *
	Saturday	3.17E-02	6.10E-02	5.21E-01	6.03E-01
	Sunday	-1.80E-01	5.95E-02	-3.03E+00	2.44E-03 *
Average temperature		-2.23E-03	1.11E-03	-2.02E+00	4.38E-02 *
Average precipitation		-2.36E-01	4.03E-02	-5.86E+00	4.64E-09 *
Max wind speed		-2.36E-01	4.02E-02	-5.87E+00	4.41E-09 *
Max relative humidity		1.88E-03	1.72E-03	1.10E+00	2.73E-01
Time-fixed effects		1.93E-03	1.27E-04	1.53E+01	< 2E-16 *

[*] denotes significance at the $p<0.05$ threshold

"Estimate" showing the estimated values of the regression coefficients associated with each independent variable. The other columns demonstrate the standard errors and t values of each variable with the p values showing the probability of significance for the estimated value. The t statistic–or t value–measures the estimate of the regression coefficient β divided by its standard error. The larger the t value is, the more likely the estimate of the regression coefficient is different from 0. The probability of values larger than the calculated t value in a student's t distribution is the p value to signify the significance of the estimates. Typically, a p value of less than 0.05 is accepted as statistically significant.

As the results shown in Table 2 indicate, air quality alerts (OAD) did not show a significant impact on the micromobility trip counts. The average estimate on OAD was positive, suggesting that when an ozone alert was issued, the number of trips on micromobility vehicles increased on average. On the contrary, the actual air quality (AQI) had a significant effect. When the AQI elevated to an unsatisfactory level, the number of trips made on micromobility vehicles decreased. The interaction term did not show a significant effect on the micromobility trip counts, meaning that the impacts of actual air quality did not add to effects of the air quality alerts, or vice versa. The results further indicate that more trips were made on Fridays and Saturdays compared to other day types. From the estimated coefficients, except for Saturdays, the other day types show significantly smaller trip counts compared to the Friday baseline. Temperature, precipitation, and wind speed were all significant predictors of micromobility behavior. The time-fixed effects also showed a significantly positive estimate by the model, confirming the upward data trend.

Impacts of air quality alerts on different types of micromobility trips were further examined. Since the accurate geographical information about the start and end points of each trip was not available, the trip purpose could not be inferred. Thus, types were determined based on trip length. In this study, all trips were sorted by length in ascending order. It was assumed that the top 80% trips were short length. The cutoff point was 1.5 miles, which is within the range of most frequent trip distances found in other areas (Lee et al., 2019; McKenzie, 2019). Responses of both types of trips were studied using the same regression model above. The results are listed in Table 3 showing the influence of air quality alerts on the two types of trips. As can be seen, only short-distance trips show a significant reduction in response to the actual air quality (AQI) while neither type of trip is responding to air quality alerts (i.e., OADs).

In addition, a sensitivity analysis was implemented by varying the

Table 3
Impacts of air quality information on short-distance and long-distance daily trip counts

Trip Length	Variables	Estimate	p value
No. of short-distance trips	Ozone Action Day (OAD)	1.39E-02	9.16E-01
	AQI: Unhealthy for Sensitive Groups	-3.01E-01	3.12E-02 *
No. of long-distance trips	Ozone Action Day (OAD)	4.59E-02	7.47E-01
	AQI: Unhealthy for Sensitive Groups	-2.13E-01	1.60E-01

cutoff percentage threshold: 70 (short)/30 (long), 75/25, 85/15, 90/10, 95/5. The p values for the estimates of long-distance trips can be seen in Fig. 3. The figure show that for long distance trips, when trip distance gets no less than 1.3 miles (i.e., 75% threshold), the trips become insensitive to AQI information. There is a drop in p value when the trip distance is longer than 3 miles (i.e., 95% cutoff), yet the p value still suggests non-significance. In this study, a deterministic threshold is not suggested since the value may be limited in generalizability. Yet, the sensitivity analysis does support that long distance trips are insensitive to AQI information while short distance trips are.

4. Discussion

Governments have been disclosing air quality information to the public to encourage behavioral changes with a goal to promote better public health and environmental sustainability. Due to the critical role our transportation behavior plays in determining personal exposure to air pollution, this study sought to examine and evaluate the effectiveness of air quality alerts in encouraging behavioral changes on an innovative transportation mode, micromobility. The results demonstrate that people in Austin do not change their micromobility transportation usage behaviors in response to air quality alerts (OAD), echoing the driving miles results from Atlanta and Salt Lake City (Noonan, 2014; Tribby et al., 2013) and contradicting the daily cycling trip results from Sydney, Australia (Saberian et al., 2017). Conversely, daily micromobility trip counts did significantly decrease on polluted days when air quality thresholds were exceeded. The results partly agree with earlier research that people showed "averting" behaviors in response to poor air quality by staying indoors, rescheduling outdoor activities, or reducing the amount of strenuous outdoor activities in order to reduce their personal exposure to air pollution (Bäck et al., 2013; Bresnahan et al., 1997; Noonan, 2014). The findings are also in line with the results of Morton (2020) where cycling demand was significantly correlated with actual air quality.

Shorter trips in our study were more sensitive to actual air quality (AQI) than longer trips. It may relate to the purposes of micromobility trips, which may be recreational in nature or complement other transportation modes (e.g., taking an e-scooter to a mass transit station). Since the exact start and end point of each trip is unknown in our study, trip purpose remains obscure. Nevertheless, over 90% respondents in Austin indicated that they had used micromobility vehicles for recreational use and nearly 30% participants ranked recreational trips as their most frequent trip types (City of Austin, 2019). Thus, shorter trips may be more responsive to actual air quality since they are more likely to be recreational in nature and, therefore, more flexible.

Though government agencies have been delivering air quality alerts at substantial cost for decades to the public to promote public health and environmental sustainability, the results of this study suggest that the impacts of air quality alerts (OAD) on micromobility trips are limited. There are several possible reasons for the ineffectiveness of this information policy. Firstly, the Ozone Action Day is issued based on a prediction of air quality on the following day, and the accuracy of such predictions is poor (Neidell, 2012; Saberian et al., 2017). In our study period, we estimated only a 30% accuracy. The public are not typically equipped with the capability of identifying the prediction errors, but

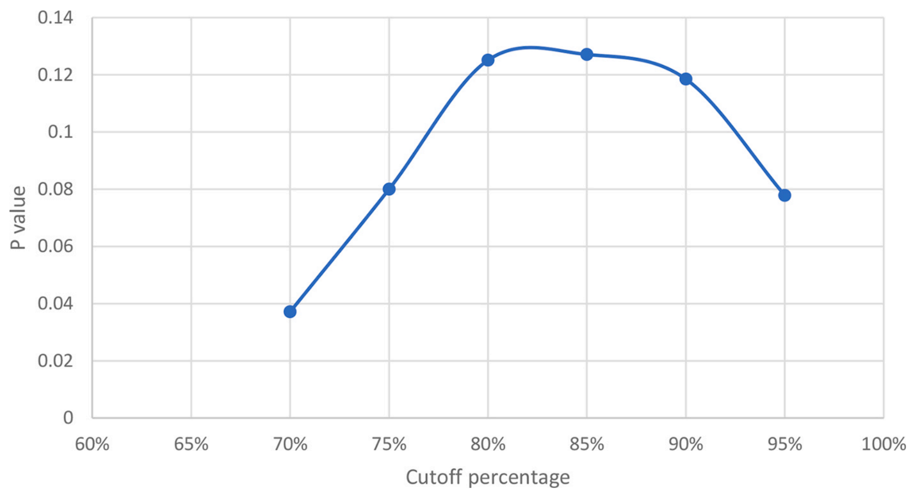

Fig. 3. p values of AQI estimates corresponding to different cutoff percentages for estimates of long-distance trips.

over time this may have damaged the public's trust towards this information. Another possible explanation is that even though the public is receiving alerts predicting ambient air quality, this information is not prioritized during their decision-making process. Instead, people may react to the actual air quality based on their perception of the ambient air quality at the time they are considering a micromobility trip. A caveat lies in the fact that judgements based on perceptions are often wrong or only correct on severely polluted days (Bäck et al., 2013; Kim et al., 2019; Schmitz et al., 2018). Lastly, the mixed messages communicated in an alert may hinder its effectiveness. In fact, the alerts not only deliver the health burdens of air pollution to the public but also call for voluntary actions to reduce emissions. Therefore, the air quality alerts try to convey the official information to dual audiences: the vulnerable groups who need to take actions to protect themselves and the general public who can help to alleviate the pollution (Petts, 2005). The two messages: staying indoors to protect yourself or utilizing more environmentally friendly transportation means, may be perceived as logically consistent, while the associated decision-making towards the two could be conflicting. For example, during moderately polluted days, vulnerable or sensitive groups are encouraged to adopt protective behaviors (e.g., not traveling) while the remaining groups are advised to use more sustainable transportation means when traveling. Such a conflicting situation might paralyze people's decision-making capability and lead them to do nothing at all (Samuelson & Zeckhauser, 1988). As air quality can be viewed as a common good, asking for collective action may also encounter the common good dilemma where people may transfer the liability of air pollution to other institutions or government (Bickerstaff & Walker, 2002) or be incentivized to free ride on the sustainability actions of others (Lubell et al., 2006).

As we are all inundated by masses of information every day, we make decisions based on how we perceive and interpret the information. Air quality information in the form of alerts (e.g., OAD) has been disseminated to the public for many years by creating the link between people and their surrounding air quality to raise awareness, increase knowledge, and ultimately persuade behavioral change. Nevertheless, even after years of joint efforts from federal and local governments, the results of this study are not promising. Despite the fact that riding on a micromobility vehicle imposes greater risks of air pollution exposure to the rider, it was found that people do not change their usage behaviors on micromobility vehicles in response to air quality alerts in Austin, TX. In contrast, it was found that the public does significantly change their usage behaviors in response to actual air quality (AQI), suggesting an opportunity for federal and local governments to disseminate real-time AQI-based information as an effective avenue towards changing people's transportation usage behaviors. With the multiple possible reasons for the inefficacy of air quality alerts, findings of this research could help with better decision making in designing information policies to facilitate public awareness and encourage behavioral changes. To achieve the goal of better public health and environmental sustainability, government agencies should carefully consider the timing, accuracy, and message clarity when distributing air quality information to the public. Government should also consider the variability in perceptions of air quality among various groups to deliver tailored information in order to facilitate awareness and group-specific engagement of the public (Schmitz et al., 2018). Carefully designed tailored feedback has the potential to influence individual travel behavioral changes towards more pro-environmental and pro-healthy ones (Ahmed et al., 2020).

5. Conclusion

For many years, both the federal and local government agencies have been committed to air quality information disclosure to inform better decision-making for the general public. One critical perspective to evaluate the performance of such an information policy is behavioral changes, among which transportation usage behavior is of utmost importance. The relatively recently emerged transportation mode of micromobility puts riders at higher risks of exposure to ambient air pollution, for which studies are lacking. To address the gap in understanding, this study examined the effectiveness of air quality alerts in the form of Ozone Action Days in influencing micromobility usage behaviors in Austin, TX. The results of this study suggest that people do not change the usage of micromobility vehicles in response to air quality alerts, while usage does significantly decrease on days of unsatisfactory air quality levels. Micromobility trips of shorter distances are more sensitive to actual air quality level than longer distance trips. The results suggest air quality alert policies (i.e., Ozone Action Days) are not reducing exposure to ambient poor air quality in this mode of transportation. As governments are trying to harness the power of information to influence the public, it is important to evaluate how the public perceives, absorbs, and reacts to the information. Such information can empower people to change and determine the direction of the change, but may also end up creating unexpected or undesirable consequences. Real-time, unequivocal, accurate, and tailored information may be more effective at evoking the desired transportation behavioral changes enabling decision makers to design more effective air quality information communication policies that promote better environmental sustainability, public health and awareness of ambient air quality.

This study faces several limitations which need to be addressed in future research. Firstly, the study period in this paper could be extended. Micromobility is a relatively new transportation mode to achieve widespread use. In our case, we stopped analysis of data when restriction policies (e.g., geofencing) began to impact the usage of micromobility vehicles. Further, behaviors towards this innovative transportation mode are subject to many variables, such as policy interventions, making it difficult to capture the variation in micromobility data. Additionally, the social context may limit the generalizability of this study. People in different areas may use the micromobility vehicles for different purposes, and the structures of transportation systems over which micromobility vehicles travel may vary sharply. Thus, the behavioral responses may be disparate across different metropolitan areas. Future research needs to examine the external validity of the findings in this work by studying the transportation behavioral responses under different social and infrastructural contexts. Lastly, we used the daily trip counts as a proxy for micromobility usage behavior. Future research is needed to the role of demographics, to access exact start- and end-point data, and to collect individual-level trip data to deepen our understanding of micromobility transportation usage behavior.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2022.104025.

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