Micromobility versus Driving: How Air Quality Alerts Impact Transportation Choices

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Abstract: Previous studies have shown that responses to information on poor air quality are more discernible on active transport than on driving. However, it is unclear whether the differences in responses stem from the differences between the characteristics of transportation modes or the social context–related factors. We conducted a comparative study to evaluate the effectiveness of air quality alerts in influencing the usage of different transportation modes, namely, micromobility and driving. An examination of over 6.9 million micromobility trips and 3 million traffic counts revealed that usage behaviors on both transportation modes do not change in response to air quality alerts, but both decrease during the daytime of a polluted day. The findings suggest that several social context–related factors matter to the success of air quality alerts, including the overall societal attention/awareness of air quality and the coverage and access to more sustainable transportation modes to empower the public. **DOI: 10.1061/JMENEA.MEENG-6168.**

Author keywords: Air pollution; Air quality alerts; Driving; Micromobility; Replacement.

Introduction

Despite decades of efforts, the fight to reduce air pollution is still far from over in the US, even though extreme periods of pollution have been reduced. Over 40% of the population still lives in areas with unhealthy levels of air pollution (American Lung Association 2018). It has been widely acknowledged that air pollution can lead to premature morbidity or even death. What is worse, it also imposes disproportional burdens on susceptible groups like women, children, and low-income families.

Due to the central role played by transportation behavior in air pollution and personal exposure (Tran et al. 2020) and the goal of changing people's behaviors in response to air quality information, it is critical to understand the responses to information on poor air quality across various transportation modes. Ahmed et al. (2020) found that customized pro-environmental travel plans successfully promoted individuals' transportation choice toward more pro-environmental and pro-health ones. A deeper understanding of which modes are more sensitive to air pollution information can enact targeted strategies and measures to be carried out to promote environmental sustainability and public health through more informed decision-making. This paper uniquely examines two main modes of transportation namely, active transport (i.e., human-powered mobility, such as biking or walking) and driving, and their usage responses to poor air quality information. The results contribute insights into impacts of air quality information policies on transportation behavior and ultimately promote environmental sustainability and public health.

The paper structure is as follows: the existing literature on how active transport and driving have responded to poor air quality information is summarized in the following section. Next, the design of this study, including data collection and statistical analyses, are presented. The data summary and results of statistical analysis are detailed and followed by discussion of the findings and areas for future improvements. The last section provides conclusions of the key findings of this work and provides policy recommendations.

Literature Review

Impacts of Air Quality on Active Transportation and Driving Behavior

Previous studies have suggested that the level of usage of active transportation vehicles may be influenced by information on poor air quality. It was found that the amount of cycling reduced substantially when an air quality alert was issued in Sydney, Australia (Saberian et al. 2017). It was also found that hazy weather could significantly change cycling behaviors in Beijing, China (Zhao et al. 2018). The correlation between air quality and cycling behavior was investigated by (Morton 2020) in London. The study observed that a rise in particulate matter with diameters that are 10 micrometers and smaller (PM10) levels led to an increase in cycling trips, whereas elevated ozone levels were associated with a decrease in cycling demand. As suggested in the study of Xu et al. (2022), the number of micromobility trips was significantly associated with air quality measures, where the counts on micromobility vehicles decrease when the actual air quality falls below satisfactory level, i.e., an Air Quality Index (AQI) no more than 100. A study from Ribeiro et al. (2022) developed a method to generate such health-oriented routes for active transport participants like pedestrians and cyclists with less pollution and noise exposure.

Compared with the significant correlation identified between active transport modes and air quality information, findings on the impact of air quality information on driving behavioral responses

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Note. This manuscript was submitted on January 23, 2024; approved on July 19, 2024; published online on October 25, 2024. Discussion period open until March 25, 2025; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Management in Engineering***, © ASCE, ISSN 0742-597X.

were more pessimistic in terms of them being able to influence behaviors. Henry and Gordon (2003) discovered that on days with air quality alerts in Atlanta, government employees drove significantly fewer kilometers, but there was no impact on the number of daily driving trips or kilometers driven by other groups. Cutter and Neidell (2009) found that air quality alerts in the San Francisco Bay area led to a significant reduction in daily traffic volume but did not affect the use of public transit. In Salt Lake City, Tribby et al. (2013) investigated the impact of air quality alerts on traffic volume and found no significant changes overall, but observed decreases in traffic downtown and increases in the outlying mountain areas. Across over 300 cities in the US, Noonan (2014) found only weak evidence to support the idea that air quality alerts resulted in decreased driving time. The differences in responses on the two transportation modes may develop from the characteristics of each mode, motivating the comparative study in this work.

Balancing Health, Environment, and Mobility Choices

The urban transportation landscape is rapidly evolving, shaped by emerging trends such as mobility-on-demand services. The significance of data-driven approaches to accommodate those changes has been emphasized due to the complex interactions among urban infrastructure, traffic patterns, and technology (Wang et al. 2022), which aligns with our examination how urban dynamics influence responses to air quality alerts. Researchers have identified significant public health and environment benefits of shifting from cars to active transport (Brand et al. 2021; Rodrigues et al. 2020), which involves more physical activity and less emissions. However, active transport users face the risks of air pollution exposure, which may erode the health benefits provided by physical activity. In addition, active transport can induce a higher level of inhalation dose compared with driving (Cepeda et al. 2017).

Micromobility riders are also susceptible to inhaling surrounding air pollution, much like cyclists. Micromobility trips tend to take place in areas of high traffic concentrations, such as city centers, which means that riders are more likely to be exposed to air pollution emissions (Cepeda et al. 2017; Zhang and Batterman 2013). Previous studies have found varying levels of responses based on a set of health indicators, including pulmonary functions, inflammation, and cardiac functions, to short-term exposure to air pollution on bicycles (Buregeya et al. 2020; Cole et al. 2018). Although various studies have suggested that the benefits of active transport outweigh the potential risks, it is important to acknowledge that individuals who make the switch from cars to active transport may bear a disproportionate amount of exposure to air pollution (Gelb and Apparicio 2021). Therefore, the significant relationship between information on poor air quality and behavioral changes on active transport may arise from the desire of users to avoid air pollution exposure.

On the other hand, gasoline-powered vehicles impose threats to both the environment and public health. The role of transportation emissions in contributing to overall air pollution has long been acknowledged, and the pollutants found in vehicle exhaust have been strongly linked to increased morbidity (Samoli et al. 2016). In 2015, it was approximated that nearly 385,000 fatalities and $1 trillion in health-related expenses were linked to air pollution caused by tailpipe emissions (Anenberg et al. 2019). The pollutant concentration levels in automobiles may even be several times higher than that of active transport, although the higher inhalation doses on active transportation makes the overall air pollution exposure between the two modes comparable (Cepeda et al. 2017; de Nazelle et al. 2012).

The enclosed cabin of cars may provide drivers with a sense of protection when faced with air pollution outside. However, the reality depends on the quality of air filtration in a given car (Morales Betancourt et al. 2017). The resistance to behavioral changes on driving might derive from a potentially misguided sense of protection from air pollution. Therefore, the choice of daily transportation mode not only has a profound impact on environmental sustainability, but also plays a decisive role in an individual's personal exposure to air pollution. Understanding the transportation behavioral responses on different modes to information on poor air quality may enable policymakers to carry out more informed strategies and tailored decisions to reduce emissions and improve human health.

Research Gap and Objectives

Previously published studies are limited in generalizability by only investigating a single transportation mode response to information on poor air quality. Therefore, this makes it unclear whether the differences between the responses on different transportation modes stem from the characteristics of the transport mode or from the social context of the study area. To isolate the possible impacts from the social context of the study area, it is necessary to evaluate the responses on multiple transport modes to air quality information in the same geographical region over the same time period. Micromobility is becoming one of the most popular active transport modes in the US, although driving remains the most predominant mode of transport.

Therefore, the objective of this research is to conduct a comparative study and evaluate the effectiveness of air quality alerts in influencing the usage of different transportation modes, namely micromobility and driving. Building upon a micromobility usage study based in Austin, Texas (Xu et al. 2022), the objective of this study is to examine the responses on driving behavior to air quality information in the same city, namely Austin, Texas.

Previous studies have also suggested potential existence of switching from one mode to another when facing information on poor air quality. Cutter and Neidell (2009) found the traffic volume of driving decreased significantly in the morning, whereas the transit counts only showed slight increases on days with a Spare the Air alert. It was found that shared micromobility (using publicly accessible human-powered vehicles such as manual bikes, e-bikes, and e-scooters for short trips) is replacing other transport modes such as walking, public transit, and even biking and driving (Weschke et al. 2022; Ziedan et al. 2021). Things can become problematic if people act out of self-interest by choosing not to ride a bike or scooter but switching to driving instead when believing the air quality is poor, which in turn exacerbates the traffic and air quality. Other researchers found that people with various socioeconomic background might replace their cycling with other modes differently such as public transit or cars (Zhao et al. 2018). This study will assess the spatiotemporal responses and possible existence of replacement effects between the two modes of transportation.

Methodology

Data Collection

This study examined micromobility usage and traffic volume data, air quality data, and a series of other possible confounding parameters in the research setting of Austin, Texas, to compare the responses to information on poor air quality between micromobility usage and driving and investigate the spatiotemporal distribution of transportation behavior on the two modes in order to examine the possible existence of replacement effects. Due to combined efforts of deployment of advanced metering infrastructure (AMI) and the efforts to make data open to the public, Austin's open data portal offers opportunities for research activities through a rich collection of administrative data.

The city of Austin stands out as one of the few in the US that requires micromobility companies to disclose their data. Given its significant system size of scooter sharing, this study collected and analyzed data on shared dockless scooters and e-bikes in Austin. The city's Transportation Department provided the data through an open data portal, which included information on each trip made by these micromobility vehicles in the Austin area from April 2018 to September 2019. The data set, which is updated daily, contains various details on each trip such as the unique device ID, vehicle type, trip duration, distance, start and end time, and start and end census tracts. The study excluded abnormal records that had trip duration times below 0 or above 24 h or trip distances outside the range of 0.16 km (0.1 mi) to 804 km (500 mi), as recommended by the Austin Transportation Department. After aggregating the data on a daily or hourly basis and excluding extreme daily trip counts due to citywide events or festivals, over 6.9 million micromobility trips were analyzed within the study period, which ended in September 2019 to avoid any geofencing policies.

Traffic counts data from 16 (out of 19) radar sensors installed across the city were also provided by the City of Austin Transportation Department (City of Austin Transportation Department 2020). Three sensors were excluded due to incomplete sensor information or abnormal data patterns. Locations of sensors can be observed in Fig. 1.

The radar sensors measure traffic volume in each lane at the installed intersections every 15 min across Austin. Each record contains the sensor ID, lane ID, reading time, and traffic volume. Over 3 million records were generated during the same data collection period as the micromobility data.

The data were cleaned prior to being aggregated at a daily or hourly basis. Traffic counts of each sensor every 15 min were obtained by adding up counts of lanes monitored by the same sensor. Some sensors had multiple readings in a single 15-min time bin, and we averaged the value within the same interval. As for addressing missing data in the traffic counts, we applied a multivariate

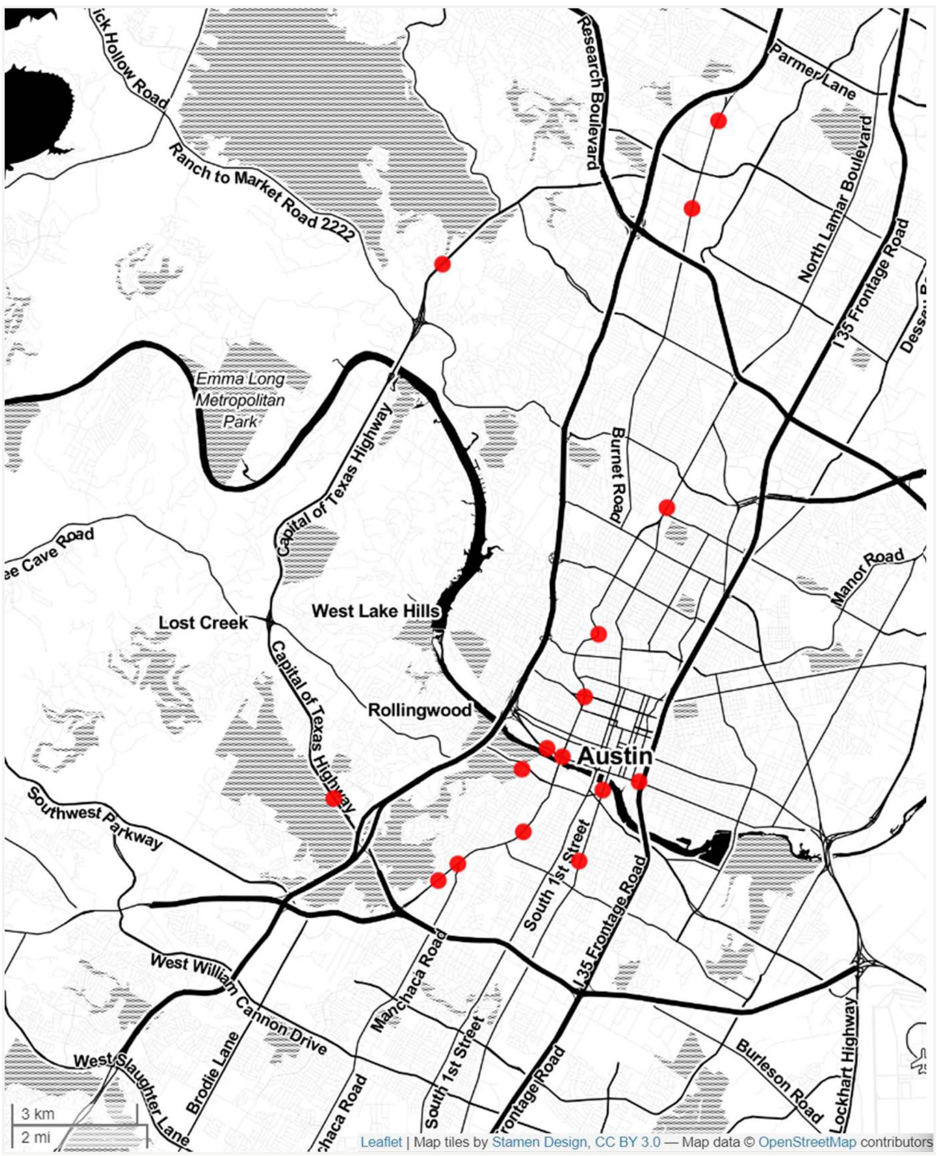

Fig. 1. Locations of traffic volume sensors (indicated by dots). (Basemap Leaflet. Map tiles by Stamen Design, CC BY 3.0–Map data © OpenStreetMap contributors.)

imputation by chained equations (MICE) to impute the missing values. MICE assume the missing data are missing at random (MAR), which means that the probability a value is missing depends on and can be predicted by other observed values (Azur et al. 2011). Distributions of original data and imputed data of each sensor were compared to validate the imputation quality. Comparisons between the density distribution of recorded data and imputed data of each radar sensor are shown in Fig. 2, where the dashed lines represent the distribution of monitored data, and the solid lines (five times imputation with different initialized values for each sensor and the average values are used for analysis) show the distribution of imputed values of traffic counts. The results suggest the distribution of imputed data align well with the original data.

In the City of Austin, an Ozone Action Day (OAD) is declared when the projected concentration of ozone on the following day exceeds the national air quality guidelines. The government notifies the public through various mass media channels (such as email, news, and social media) when an Ozone Action Day is announced. The dates of Ozone Action Days were obtained from the Austin municipal government website. Despite the long-standing existence of air quality alerts disseminated across various platforms, knowledge concerning their actual reach remains scant. An analysis of survey data from 2016 to 2018 revealed that approximately half of the adult population in the US is cognizant of these air quality alerts, with 9% of respondents reporting a decrease in outdoor activity and 2% indicating reduced driving in response to these alerts (Mirabelli et al. 2020). Television emerged as the preeminent medium for disseminating air quality alerts, followed by mobile apps/devices and the internet, including social media platforms. The choice of communication channels exhibited notable variations across different age groups. For instance, younger demographics displayed a preference for obtaining information via mobile apps, whereas the older segments leaned toward television as their primary source of information (Tompkins et al. 2022).

To ensure that the effects of actual air quality were taken into account, monitored air quality data were gathered from the US Environmental Protection Agency's *Air Quality Index Daily Values Report* (USEPA 2023b). The overall AQI is determined by the concentrations of five pollutants that are regulated by the Clean Air Act: ground-level ozone, particle pollution, carbon monoxide, sulfur dioxide, and nitrogen dioxide. In the US, the AQI ranges from 0 to 500 and is classified into six levels based on health concerns,

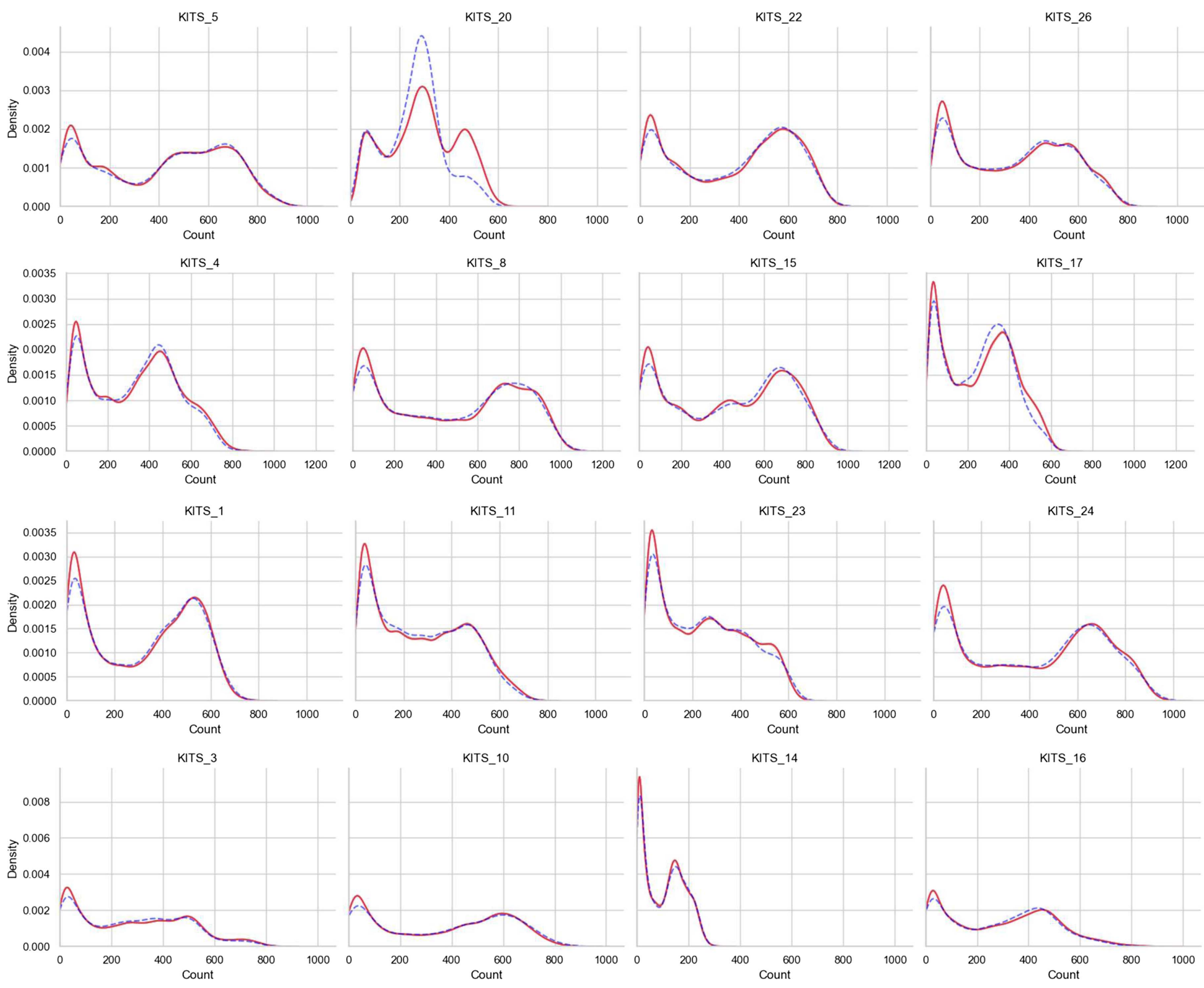

Fig. 2. Comparisons between distribution of recorded data and imputed data of each radar sensor. Dashed lines indicate monitored data; solid lines indicate imputed data.

each represented by a different shade. This system aims to increase public awareness and understanding. The AirNow website maintained by the US Environmental Protection Agency provides basic information about AQI categories (USEPA 2023a). Typically, when the AQI value is below 100, corresponding to the Good or Moderate levels of health concern, the air quality is considered satisfactory and the health impacts are considered minimal.

Ozone and PM2.5, two prominent secondary pollutants formed from primary emissions associated with traffic, were the principal contributors to AQI values exceeding 100 during the study period. Specifically, the transformation of primary pollutants such as nitrogen dioxide (NO_2), emitted directly by vehicles, plays a crucial role in the formation of ozone and particulate matter through chemical reactions in the atmosphere. These pollutants typically exhibit insignificant spatial variability within the same area, thus establishing a consistent profile of traffic-related air pollution. Air quality data were gathered from four monitoring stations strategically situated in proximity to the city's central district, an area with the highest concentration of micromobility trips. Therefore, it is justified to use the monitored air quality data to represent the average air quality across the study area.

To control potential confounding variables affecting both air quality and transportation behavior, meteorological data were collected for the study period. The weather information was obtained from a weather station located at Austin-Bergstrom International Airport and included measurements of average temperature, maximum wind speed, relative humidity, and precipitation. These parameters were selected for analysis given their potential impact on air quality and transportation behavior. Data on meteorological conditions were obtained from Weather Underground (Weather Underground 2021).

Statistical Analysis

To first estimate the driving behavior responses to air quality alerts, daily traffic counts were examined through a multivariate Poisson regression. Next, to identify possible replacement behavior at higher granularity, both micromobility and driving traffic counts were aggregated at an hourly level and traffic counts were further analyzed per intersection (i.e., per sensor). The regression model can be expressed

$$\begin{aligned}\text{Log}(transportation\ behavior_{l,t}) &= \beta_0 + \beta_1 \times \text{OAD} + \beta_2 \times \text{AQI} + \beta_3 \times Day\ Type \\ &\quad + \beta_4 \times interaction(\text{AQI}, \text{OAD}) \\ &\quad + \sum_i \beta_i \times Meteorological\ parameter(i) + \varepsilon\end{aligned}$$

Three dependent variables were modeled: daily traffic counts in Austin, hourly traffic counts (t) at each monitored intersection (l), and hourly micromobility trips counts. The main independent variable of interest is a binary variable indicating the issuance of an OAD alert. The model adjusts for the potential confounding effects of monitored air quality (AQI), meteorological factors, and day of the week (categorized as Monday to Thursday, Friday, Saturday, Sunday, and federal/state holiday). Furthermore, we examined the interaction between the OAD alert and actual air quality by including an interaction term in the model.

Results

The spatial distribution of the micromobility trips are explored and plotted in Fig. 3, indicating the number of trips made within each

Fig. 3. Spatial density of micromobility trip counts across census tracts in Austin, Texas. Locations of traffic counts sensors are indicated by dots. (Basemap Leaflet © OpenStreetMap contributors © CARTO.)

census tract in Austin along with locations of traffic count sensors as dots in the zoomed-in inset map. As the figure shows, most of the micromobility trips occurred concentrated in the downtown area of Austin, especially in the single central census tract, where over 2 million trips took place during the study period. The traffic count sensors are located in the areas with the highest numbers of micromobility trip counts, enabling comparisons between the two modes.

As for the traffic volume data, the same regression model was applied to the total daily traffic counts collected across 16 Austin intersections during the study period. Because the traffic counts trend is more stable over time than for micromobility vehicles, the time-fixed effects were not included into the model. The results of the regression model are given in Table 1. In the Variables column, the independent variables are listed and their estimated regression coefficients are displayed under the Estimate column. The standard errors and *t*-values for each variable are shown in the other columns, with the *p*-values indicating the probability of the estimated value being significant. The *t*-value is obtained by dividing the estimated regression coefficient β by its standard error and reflects the likelihood of the estimate being different from zero. A larger *t*-value suggests a higher probability of a significant difference. The *p*-value represents the probability of observing values as extreme as the calculated *t*-value or more extreme in a student's *t* distribution and indicates the significance of the estimated values.

The results in Table 1 indicate that the traffic counts were mainly predicted by day type and meteorological measures (i.e., temperature and precipitation), and neither air quality alerts (OAD) nor actual air quality (AQI) showed a significant influence on the total daily traffic volume in Austin. To provide a more detailed analysis, the spatial-temporal effects of air quality alerts on traffic volume and micromobility usage were analyzed by fitting the aforementioned model with hourly data (per intersection or per sensor for traffic volume). Compared with the traffic counts results, the micromobility results suggest that air quality alerts do not impact the usage of micromobility vehicles, although the usage does decrease significantly when the actual air quality gets worse, especially for short-duration trips (Xu et al. 2022).

Fig. 4 shows the hourly impacts of air quality alerts (OAD) at an individual sensor level, with the last column indicating the hourly impacts on total traffic volume. Positive coefficients indicate increases in traffic volume; negative suggest decreases. Significant hours ($p < 0.05$ level) are boxed with a dark border. As the figure shows, air quality alerts induced systematic but not significant increases in traffic volume during the daytime and the increases became significant around noon at seven intersections.

Table 1. Results of traffic counts regression analysis during the study period

Variables	Estimate	Standard error	*t*-value	*p*-value
Ozone action day (OAD)	0.026	0.025	1.030	0.303
AQI: unhealthy for sensitive groups	−0.025	0.027	−0.926	0.355
Interaction (AQI, OAD)	0.012	0.052	0.232	0.816
Day type				
Holiday	−0.321	0.024	−13.600	<0.001*
Monday to Thursday	−0.068	0.010	−6.660	<0.001*
Saturday	−0.185	0.013	−14.700	<0.001*
Sunday	−0.354	0.013	−28.000	<0.001*
Average temperature	0.000	0.000	1.930	0.0532**
Average precipitation	−0.029	0.010	−2.970	0.0029*
Maximum wind speed	0.001	0.001	1.030	0.306
Maximum relative humidity	0.000	0.000	−0.492	0.622

Note: *Significance at 0.05 threshold; and **significance at 0.1 threshold.

Fig. 5 shows the hourly impacts of AQI information at an individual sensor level, with the last column indicating the hourly impacts on total traffic volume. As the figure suggests, when the AQI exceeded the satisfactory threshold (i.e., values greater than 100), indicating deteriorating air quality, there was a distinct pattern in traffic volume across the city: traffic volume before 5:00 a.m. increased, whereas daytime traffic counts decreased. Responses varied among different sensors: traffic counts decreased around noon at most sensors; some sensors showed significant reductions in the mornings, but others showed reductions in the evenings.

Fig. 6 shows the results of hourly responses of micromobility usage to air quality alerts (OAD) and actual air quality (AQI). The results indicate that the usage of micromobility vehicles decreased systematically but not significantly on days with an air quality alert. At the same time, the usage of micromobility vehicles decreased significantly during the daytime during a polluted day (AQI).

Discussion

Governments disseminate air quality information to the public to persuade behavioral changes with a goal to promote better public health and environmental sustainability. Transportation mode choice, which plays a critical role in both air pollutant emissions and an individual's personal exposure to pollution, is a key element in efforts to combat air pollution. Understanding how the public responds to air quality information offers an opportunity to inform decision-making for policymakers. Examining the spatiotemporal distribution of the responses can further provide insights into the effectiveness of existing air quality information policies.

Although it has been suggested that changes on active transport may be more discernible than driving in response to information on poor air quality, previous research is limited in generalizability where only one mode was studied, making it difficult to tell whether the differences come from the characteristics of the mode itself or the social context of the study area. This study provides a comparison between the responses from micromobility usage and driving volume to air quality information in the city of Austin, Texas. Understanding the spatiotemporal distribution of the responses can improve granular performance of the existing air quality information policies.

The results showed that the daily traffic volume in Austin did not exhibit any significant correlation with air quality alerts (OAD), which is in accordance with the nonsignificant responses on micromobility vehicles and echoes the findings of previous studies (Noonan 2014; Tribby et al. 2013), contradicting the findings that people spent less time walking outdoors when there is an ozone alert in South Korea (Kim et al. 2020). Notably, although nonsignificant, the results suggest that the daily traffic volume is positively associated with air quality alerts.

Examining the spatiotemporal distribution of the responses from traffic volume data provides insights into how the behavioral responses vary across time and space and can assist with more informed decision-making. Findings of the spatial-temporal analysis further indicated that traffic volume during the daytime of alerted days systematically increased, and the increases became significant around noon at several intersections. Comparatively, the hourly micromobility usage showed systematic but not significant decreases during the daytime of alerted days. The opposite directions of changes might suggest not only the ineffectiveness of air quality alerts but also the counterproductiveness of the policy, where people switch to more-polluting means of transportation. Yet, due to

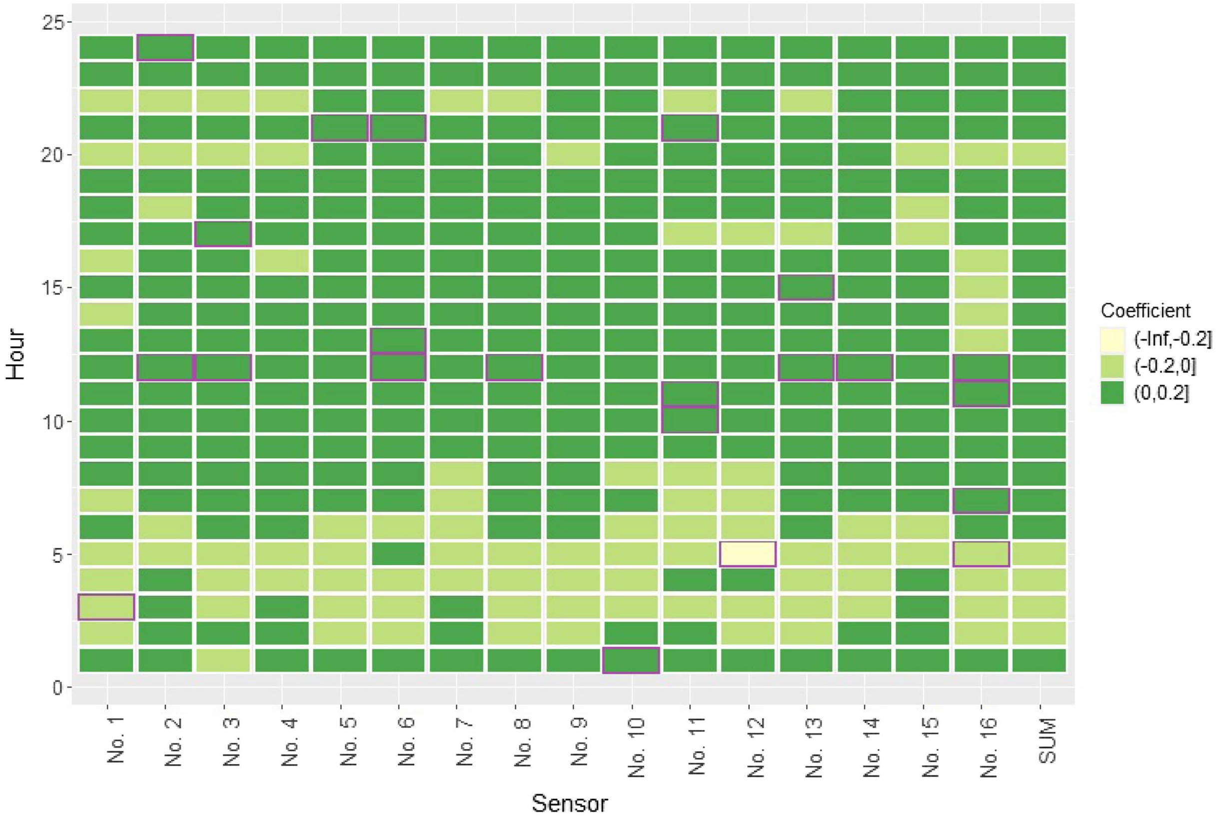

Fig. 4. Hourly impacts of air pollution alerts at individual sensor and whole city levels. SUM = total traffic volume response; boxes with a dark border indicate significance at the $p < 0.05$ level.

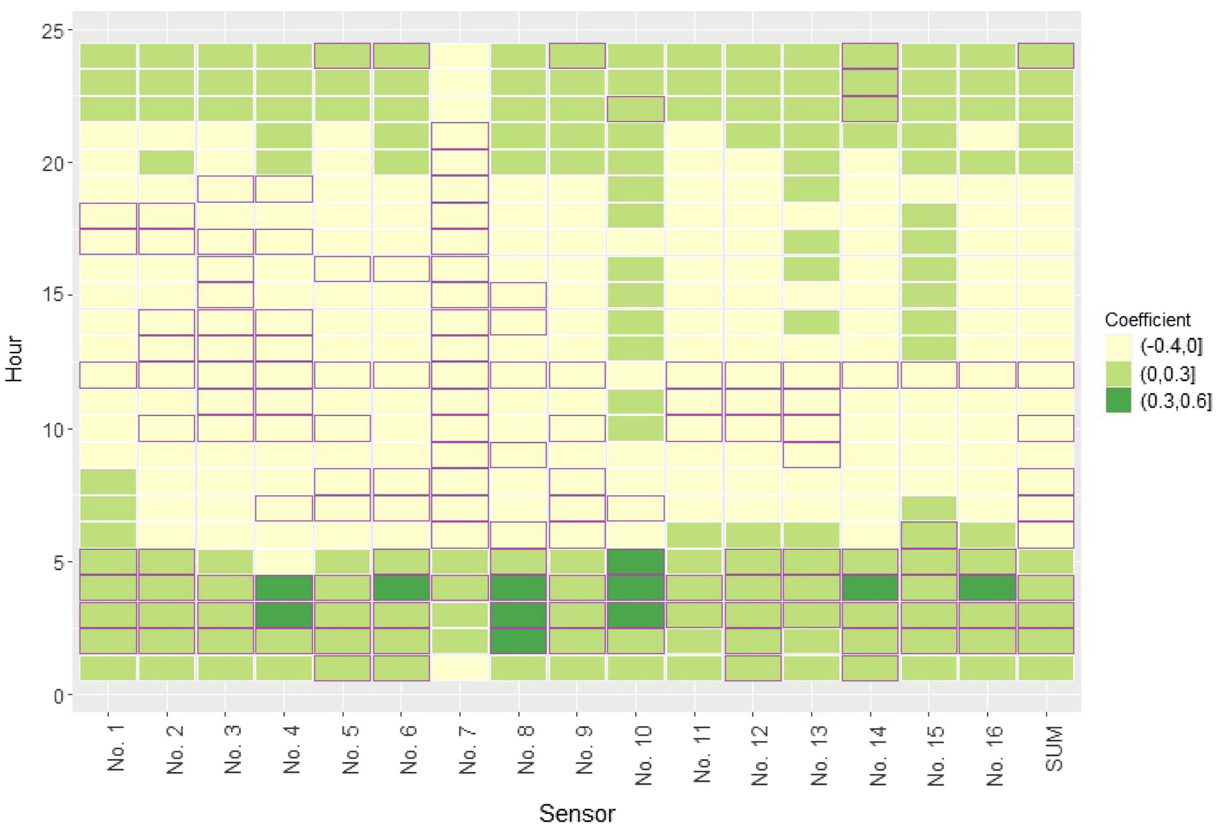

Fig. 5. Hourly impacts of AQI information at individual sensor and whole city levels. SUM = total traffic volume response; boxes with a dark border indicate significance at the $p < 0.05$ level.

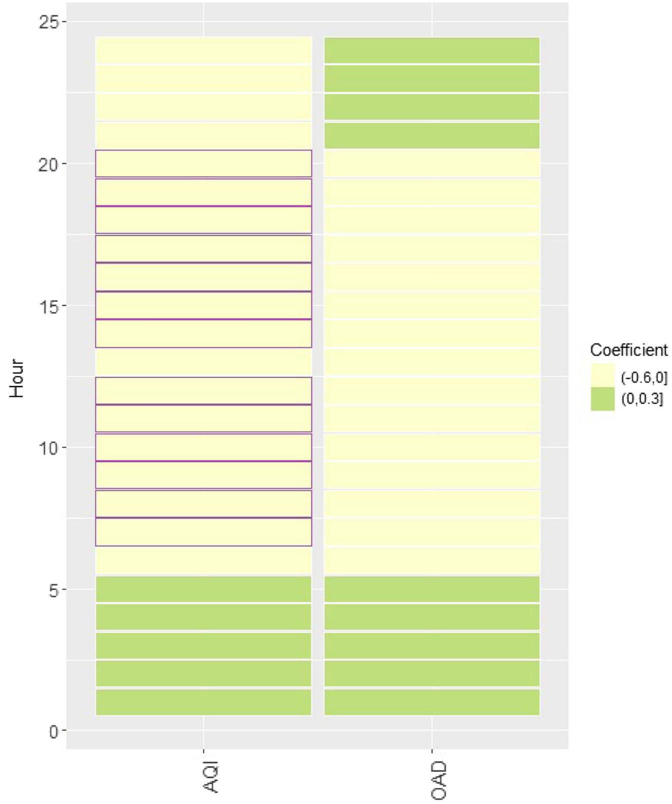

Fig. 6. Hourly responses of micromobility usage to air quality alerts (OAD) and actual air quality (AQI). Shading of boxes indicates the direction of changes; boxes with a dark border indicate significance at the $p < 0.05$ level.

the insignificance of the estimates, those arguments are more conjectural than conclusive.

As for responses to actual air quality (AQI), the responses from daily traffic volume did not suggest any significant correlation. The spatiotemporal analysis tells another story, where the traffic volume did significantly increase the night before actually polluted days compared with the traffic volume during the night before nonpolluted days. This may indicate a reverse causality, which means that instead of the pollution leading to more driving at night, it is possible that the increases in traffic volume during the night contributes to the poor air quality.

In accordance with the significant reduction in usage on micromobility vehicles (Xu et al. 2022), traffic volumes at multiple intersections dropped significantly during the daytime of polluted days. Responses on the usage of micromobility vehicles followed the same pattern, where the drop in hourly counts was significant only during the daytime. The results are in accordance with the results presented in the review by McCarron et al. (2023) that increases in air pollution are associated with decreases in physical activity. Contradictory to the findings of previous research where the responses on the active transport differ from those on driving when facing information on poor air quality (Morton 2020; Noonan 2014; Saberian et al. 2017; Tribby et al. 2013; Xu et al. 2022), the results of this study suggest that usage of both transportation modes did not respond to air quality alerts but exhibited reductions during the daytime when the actual air quality is poor.

Behavioral changes on both transportation modes were in the same direction, namely decreasing, indicating that actual air quality or real-time monitored air quality information shows potential to engender avoidance behaviors to achieve better public health and environmental sustainability. It is also possible that people identify the pollution through personal cues like sensory and health cues (Oltra and Sala 2014). The message delivered with AQI, namely, level of health concerns, or the perceived sensory or health cues on a polluted day, acts as an unequivocal communicator toward persuading avoidance behavior. Therefore, although air quality alerts fail to persuade behavioral changes that they are intended to, real-time air quality information does appear to better engage the public.

The findings of this study suggest that the previously identified opposite responses from active transport and driving may not stem from the differences between the characteristics of the two transportation modes because the results show that the responses on both modes align with each other. Responses on both modes showed no significant relationship with air quality alerts, indicating unsatisfactory performance of longstanding information communication policies. To make things worse, the results of this study show that the air quality alerts may not only fail to persuade behavioral changes but lead to counterproductive outcomes, where, although nonsignificantly, people replace their active transport with driving when there is an air quality alert. The message incorporated in air quality alerts tries to communicate with a dual audience: the susceptible groups who are at higher risks and may adopt avoidance behaviors, and the remaining general public, who can help to alleviate the pollution by switching to a lower emission mode (Petts 2005). Therefore, the public may act out of self-interests to protect themselves from pollution exposure or altruism to alleviate pollutants emission.

Switching from an active transport mode to driving echoes the findings from Wu and Geng (2020) that when people are aware of ambient air pollution, the intention to adopt pro-environmental behaviors decreases. It also agrees with Zhao et al. (2018), who found that although some groups may substitute cycling with public transit, the majority of people indicated they would turn to driving instead. Thankfully, the silver lining is that the actual air quality (AQI) acts as an alternative by providing real-time and unequivocal air quality information, agreeing with the findings of Xu et al. (2021) that people's travel behavior correlates with AQI increases.

By ruling out the possible contribution of the characteristics of transportation mode, there are a few social context–related reasons for the why air quality alerts may fail to engage transportation behavioral changes. Governments have been disseminating air quality alerts for years and the public engagement may have dissipated over time. Previous studies have identified that the effectiveness of the air quality alerts may decrease after the first alerted day when the alerts were issued consecutively for more than 1 day, which was called "alert fatigue" (Noonan 2014; Saberian et al. 2017). Therefore, after years of alerts dissemination, the public may get "fatigued" and feel powerless toward making a difference about air pollution. It was also found that simply providing the participants with air pollution information may not elicit behavioral changes without providing more personalized messaging (Haddad and de Nazelle 2018).

Moreover, in order to persuade the public to change their transportation choice or behavior, especially to more sustainable ones, the public should be provided with convenient alternative choices such as easy and affordable access to public transit and safe and dedicated bike lanes, which can also lead to less air pollution exposure compared with mixed-use lanes (Mitsakou et al. 2021).

Public awareness of air quality and the long-term local air quality can also play a part. Awareness and attention to air quality have been identified as important predictors of preventive behaviors (Oltra and Sala 2018). People living in areas with more frequent severe air pollution incidents may be more responsive to such alerts, like regions with frequent wildfires such as California and Australia (Cutter and Neidell 2009; Saberian et al. 2017) because during those events, air pollution becomes visible and perceivable with the occurrence of smoke, fire, dust, and sickness. The incorporation of real-time, participatory data collection could potentially promote the way cities disseminate and utilize air quality alerts based on the principals from the study of Ham and Kim (2020). This could lead to more targeted and effective strategies in influencing transportation choices.

On the other hand, people living in areas with overall good air quality like the study area may not pay as much attention to air quality as those who live in areas with long-term air pollution issues. The overall public perception of self-efficacy and willingness to engage in behavioral changes to improve the ambient air quality as well as the readiness of transportation infrastructure should all be carefully investigated to better evaluate the performance of air quality alerts.

This study offers a spatiotemporal comparison of travel behavior for two transportation modes in response to air quality information in the same geographical area, which was not well studied before, with the goal of informing better choices for decision makers about how to communicate and deliver air quality information. Nevertheless, this study faces several limitations that need to be addressed in future research. Firstly, this study only compared the responses from two transportation modes. Examining the responses on other modes of transportation like public transit and ride sharing can further extend and validate this study. Second, the monitored data were not at the individual level. Although the results suggest people might switch from micromobility to driving, individual-level data can further validate this proposition and enhance the robustness of this study. Future studies may harness the merits of individual-level data to inform decision makers to design tailored messages.

Conclusions

The choice of transportation mode plays a critical role in determining both the air pollution emissions and personal levels of exposure. Therefore, understanding the responses on different transportation modes to air quality alerts can provide policymakers with insights into the performance of policies and inform better decision-making to engage the public into behavioral changes and ultimately achieve the goal of environmental sustainability and public health. Due to scant research that compares the behavioral changes on more than one transportation mode, this study aimed to address the gap by comparing the responses from usage of micromobility vehicles and driving with information on poor air quality, and then analyzing the spatiotemporal distribution of the behavioral changes to better understand the effectiveness of engaging the public through various types of information.

The results showed that behaviors on both transportation modes do not change in response to air quality alerts, but the actual air quality may serve to engage behavioral changes. The results do not show any evidence of replacement behavior on a polluted day, but they do indicate a potential but nonsignificant existence of replacement from micromobility vehicles to driving on alerted days. Because the responses to air quality alerts do not vary by different transportation modes, the findings suggest that in addition to the technique adopted in the information communication, several social context–related factors matter to the success of air quality alerts, including the overall societal attention/awareness of air quality and the coverage and access to more sustainable transportation modes to empower the public.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request, including traffic volume data, micromobility data, and weather and air quality data.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant No. 1837021. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors alone and do not necessarily reflect the views of the National Science Foundation or the China Scholarship Council.

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