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Understanding the Relationships Among E-scooter Ridership, Transit Desert Index, and Health-Related Factors

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Abstract

This study aims to analyze electric scooter (e-scooter) markets in transit deserts and oases in the U.S. The four cities of Austin, Chicago, Portland, and Minneapolis were selected as case studies to determine the prevalence of e-scooter rides as related to locations with limited public transportation options. A t-test was performed to analyze the difference in the number of e-scooter rides between the transit deserts and transit oases. Overall, the arithmetic means of the e-scooter rides between the transit deserts and transit oases were not significantly different in Austin, Chicago, and Portland. The results confirm that the transit index score was among the top three predictors of trips in Austin, Minneapolis, and Portland. In Chicago, health-related characteristics such as crude prevalence of arthritis, diabetes, and obesity were found to be the most important predictors of trips in Chicago.

Keywords

public transportation, planning and development, GIS, sustainability and resilience, transportation and society, community resources and impacts, health and well-being, equity in transportation, micro-mobility and active transportation

Today, most American urban areas are adequately covered by transit services. However, many regions have less development where local streets are not connected to main arterials through public transit, so the residents are likely to be automobile oriented (*1*). These areas' unique structures and forms generally affect accessibility to transit services, consequently creating the regions designated as "Transit Deserts" (*2*). Transit deserts are a concept introduced by Jiao and Dillivan (*3*) based on the popular concept of food deserts. A food desert is an urban area where people have limited access to healthy food because of increasing suburban sprawl (*4*). Likewise, a transit desert is an area of people who have limited transportation access. The supply of transportation is related to the mass transit service of a city. High concentrations of people who rely on public transportation for their daily needs create a high demand for transit that exceeds the supply, resulting in a transit desert. Transit deserts are areas where the supply of mass transportation does not meet the demand from the population. However, if the transit supply surpasses the transit demand, then the area is a transit oasis. Transit deserts are undesirable, as people need to find alternative ways to travel to their final destination, such as relying on personal vehicles or walking (both of which could cause significant drawbacks). For instance, personal vehicles have the problem of storage, maintenance, and additional road congestion. However, walking to the destination could take a significant amount of time and be dangerous in adverse weather conditions or urban obstacles such as highways, construction zones, or busy streets.

The "first mile, last mile" issue is a concept in urban planning that tries to tackle the problem of people traveling long distances inside the city. Electric scooter (e-scooter) businesses stated that e-scooters are helping to solve the final mile problem in urban public transit (*5*). The first step toward understanding this issue is recognizing that the public transportation system of each city can only maximize services for a certain amount of space

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before it becomes financially unreasonable to support. The first mile describes the beginning of a person's transportation journey, and the last mile is the final transportation step to reach the final destination. Individuals relying on public transportation might need to walk or take another secondary mode of travel to reach their final destination. However, the lack of a proper public transit system can alter the transport network connectivity in a city (*6*). For example, an individual traveling to their local light-rail station would need to take a bus or walk. If the person had absolutely no connection between the starting point and the station, they would be stranded at the origin. As reported by Bouton et al. (*7*), public transit use drops up to 90% when passengers need to walk more than half a mile to the nearest transit stop. A city has a choice of expanding the transportation routes or leaving gaps in transit accessibility to accommodate the majority. But expansion can be burdensome given the cost of additional vehicles, tracts, and employees. Sometimes the expansion might not be feasible in high density urban settings because of narrow roads or historic buildings which prevent new tracts. The average citizen cannot use public transportation to get to the exact location they wants to go. Walking is often not a suitably fast or direct option. In addition, every person in a city owning a car causes traffic congestion and hurts the city's economy when there are uncontrollable levels of traffic (*8*). Services such as Lyft and Uber have been seen as a solution to the first- and last-mile problem. However, they contribute around 14% of traffic in some cities, a burden which is expected to grow over time (*9*). A recent possible resolution to the first- and last-mile problem is the use of micro-mobility transportation. Micro-mobility includes any lightweight device that is ideal for short trips (*10*). The popularity of micro-mobility devices has risen in recent years as e-scooters have become mainstream (*11*). E-scooters might benefit the public transit system and close the gap in first- and last-mile transportation. As such, e-scooters could be providing the necessary extra transit supply needed in transit deserts.

If e-scooter rides are happening more frequently in a transit oasis area than a transit desert area, the e-scooters might be used as alternative transportation. However, higher e-scooter ride numbers in transit desert areas could be showing that the use of the e-scooters is caused by the lack of transportation options. Most e-scooter companies have been claiming that the e-scooters are a fun new way for people to commute to work in the urban settings where there is a lack of transportation options (*12*, *13*). However, if there is no correlation between the number of e-scooter rides and the transit supply in either the transit deserts or transit oases, then there is a possibility that the e-scooters are not adding to the transit supply.

Previous research efforts have demonstrated there are certain conditions, such as day of the week, where e-scooter rides were more likely to take place (*14*). In addition, spatial and temporal analyses have been performed demonstrating how some locations such as restaurants and educational centers draw more e-scooter rides than others, creating specific hotspots (*10*, *15*). Furthermore, an online study found that 21% of adults would consider using an e-scooter when convenient. In addition, the person's perceived walkability and street safety were important factors in determining the likelihood of an e-scooter ride (*16*).

Major cities design their public transportation to serve major hotspots (*17*). Therefore, there could be a correlation between the location of e-scooter trips and the amount of transportation measured. The amount of transportation in a particular area can be measured by the transit desert index. The transit desert index considers the level of public transportation while normalizing it to the area's demand for transportation. Even in areas where public transportation is provided, there might be regions of high demand (such as a tourist location) that cause the area to be classified as a transit desert. E-scooters are often seen as a new mode of transportation best for filling gaps. However, even though they are easing the traffic in certain areas, they might not be being used in areas lacking public transportation. More e-scooter trips occurring within transit deserts could, therefore, be a valid sign that the e-scooters are generating more transit supply in areas with high demand for transportation options.

In addition, past works (*18*, *19*) have attempted to analyze the travel behavior and socio-demographic background of e-scooter users. Therefore, the extent to which health-related factors contribute to e-scooter usage is not clear. This gives scope to researchers to uncover underlying health issues that corresponded to the varying mobility of users. In a previous study, records of the social vulnerability of residents were measured in relation to the transit desert index by using the Centers for Disease Control and Prevention (CDC) social vulnerability index. The residents living in a transit desert have a social vulnerability index higher than the city averages (*20*). Therefore, there could be a specific variable within the social vulnerability index that corresponds well to e-scooter ridership, and this factor could predict the number of e-scooter rides better than the transit desert index. This paper, therefore, aims to address two primary questions on e-scooter ridership in the cities.

1. How and to what extent do access to high-quality transit services, socioeconomic factors, and health-related variables contribute to the number of e-scooter rides per census tract?

2. What are the differences in use of e-scooters between transit deserts and transit oases?

The remainder of this article is structured as follows: the next section summarizes the data used for the study and provides the location where the data can be accessed for future research purposes. We then describe the methodology of the study, which factors of socioeconomic variables might predict e-scooters, and the details about the function of the proposed models. This is followed by a description of the results of the results of the study and a detailed analysis of the outcomes. We conclude with a summary of the findings and the possible theoretical implications of the results.

Data

To collect data for use in this study, a list of the 200 most populated cities in the United States was created from the U.S. Census Bureau. Next, the researchers examined each city's data platform to determine whether they offer open access to e-scooter rides. Certain large major cities, such as Seattle and Los Angeles, have an Application Programming Interface (API) that allows selected researchers to access data on its e-scooter rides. The highly selective process of gaining access caused these cities not to be selected for this study. In addition, the researchers wanted e-scooter data from the cities that have start and finish locations, which adds versatility to the data sets. If a city did not provide this basic info in the terms of stop and start, then it could not be selected for the research. The origin and termination points of e-scooter trips were often arranged in a hexagon pattern along the city. In the end, the cities of Austin, Chicago, Minneapolis, and Portland were selected for this study.

In this study, we used the transit score to measure for accessibility to transit services and identification of transit deserts and oases. The transit index score was collected through the Urban Information Lab's ArcGIS online data portal (*21*). In summary, the transit supply was calculated at the census tract level, as demonstrated in Figure 1, by using the General Transit Specification Feed from Transitland, street intersection, and points of interest. The transit feed can consist of multiple forms such as tram, subway, rail, bus, ferry, funicular, or monorail. For consistency, we collected other data at the census tract level to support the analysis. The transit demand is the number of citizens who may benefit from transit services in a particular census tract, and the z-score of the transportation demand minus the z-score of the transit supply equates to the final transit desert index score (*20*). In addition, the census tracts were classified as transit deserts or transit oases based on the transit index score. A transit desert index score greater than 1

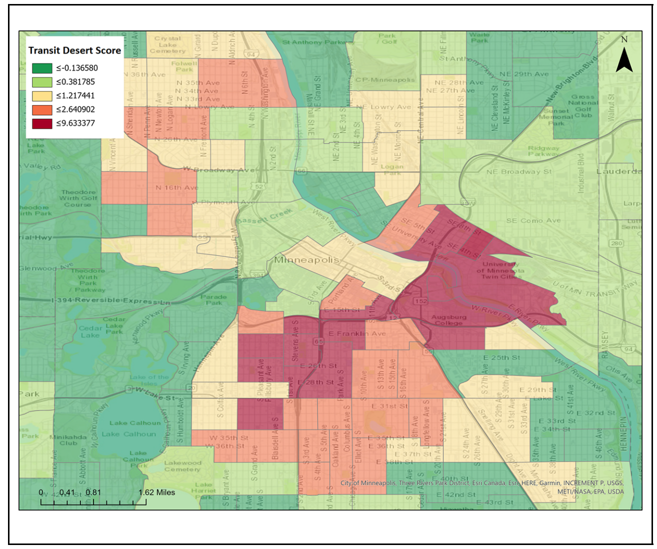

Figure 1. Transit desert map of Minneapolis, Minnesota.

denotes a transit desert area, while a score of less than 1 denotes a transit oasis. Finally, an area with a score between -1 and $+1$ is a transit adequate area (*22*).

The U.S. Census Bureau provides open access to each state's census tract data containing socioeconomic variables which can be imported into ArcGIS for further evaluation (*23*). Since the e-scooter trips were assigned to points as demonstrated in Figure 2, the points can be joined to the corresponding census tract to create a raw total number of e-scooter rides in the census tract.

Last, to establish the extent of certain variables on the effect of e-scooter trips per census tract, we used health-related variables in addition to socioeconomic factors to predict the number of e-scooter rides for each census tract. This allows the researchers to see if there was an underlying health issue that corresponded to mobility in a region. A strong correlation in a particular health category might provide detailed insight about the culture of the city that cannot be initially explained by one standard value. For example, a region with high alcohol consumption could indicate a region with an increased number of young adults in college. Furthermore, socioeconomic variables from the American Community Survey, such as income and employment status, were used to aid in the prediction. The variable descriptions and summary statistics are included in the Appendix in Tables 1 and 2.

Methodology

To answer the first research question, we proposed a random forest model to predict the number of e-scooter trips. The random forest model was chosen for a variety of reasons. First, cities might have unbalanced e-scooter trips in certain parts of the city. In that instance, one

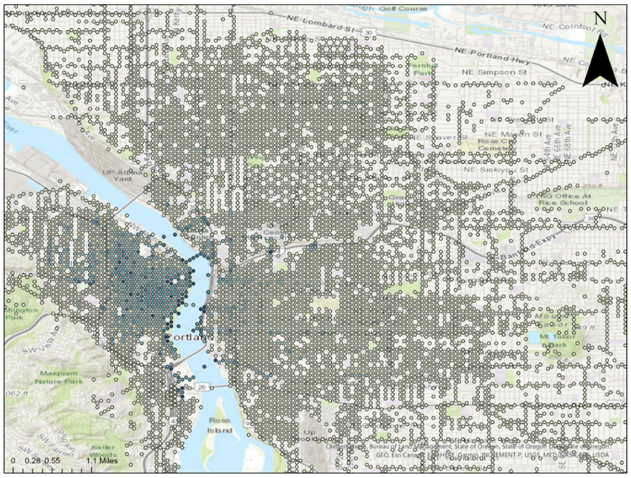

Figure 2. E-scooter points for the city of Portland, Oregon.

region may have many e-scooter trips, but its adjacent regions may have fewer trips. It is uncertain if such areas are outliers in the city's e-scooter usage. The random forest model can handle the outliers by binding them to the decision trees (*24*). In the same way, a random forest model will bind non-linear variables, which is useful for the transit desert index as it is z-scored at zero. Second, the random forest categorization will reduce the bias in the model by averaging all the variables. This means that the results cannot change widely between the final models when repeated. Also, since we are combining multiple data sets, this strategy will heavily favor the random forest model (*24*).

The random forest model produces two important numbers, which allows for the importance of each variable to be determined with regard to the ability to predict the dependent variable of the number of e-scooter rides. It is first important to note that the IncNodePurity is also known as the Gini importance. Every time a split of a node in the algorithm is made on the variable, a new Gini impurity criterion is created for two descendent nodes, where the descendent categories would be less than the parent nodes. Adding up the Gini score over the entire random forest model produces a fast variable importance ranking that is usually consistent with the permutation importance measure. The IncNodePurity may be quicker to run; however, the total amount of data for the project is smaller than typical large data projects, so the slight additional time of the result of the percent mean decrease accuracy (%IncMSE) was used for better accuracy. The random forest model algorithm computes a mean squared error for each of the variables for the number of permutations it takes to create a reliable model. That model is temporarily stored until a new model is created by a different set of variable permutations. The difference between the first and second model is taken into account by storing the results in a list, which then produces each variable's importance according to the value of the %IncMSE, where the higher the value, the better the predictor of the variable.

An important part of the random forest process is having a wide number of variables for the random forest machine model to run through. The full list of variables used is listed in Appendix Table 2. However, each variable has a reason for why it was chosen as a variable. The primary reason for most variables' inclusion was the need to evaluate the e-scooter rides on socioeconomic variables. A socioeconomic variable includes social and economic factors that fall within the categories of occupation, income, and education. Many of the variables could be categorized in multiple categories, yet some are distinct. For education variables, we choose the amount of people who have completed high school or a bachelor's degree from the American Community Survey. The income variables were gross rent, household income, and poverty. For occupation, we considered full-time employment status and uninsured status. Then, to be able to understand the full situation of the census tract, health variables such as cancer, chronic obstructive pulmonary disease (COPD), and high blood pressure were added. The goal in having multiple variables is to determine if there is a specific variable that might improve our prediction of the number of e-scooter rides.

To address the second research question, we proposed a t-test to identify whether there is a significant difference in the mean number of e-scooter rides between transit deserts and transit oases. A t-test is a statistical test used to evaluate the means of two groups. An unpaired t-test was used in the study as each e-scooter ride is independent of every other e-scooter rider. In this research, if there is no significant difference in the mean number of e-scooter rides between a transit desert and a transit oasis, the t-test will demonstrate that e-scooters are not exclusive to a particular transit category, whether it be a transit desert or transit oasis. By contrast, a significant difference in the mean number of e-scooter rides indicates that one transit category is being favored.

The raw number of e-scooter rides of each census tract was divided by the census tract area to create the dependent variable of "Rides by Area." The number of e-scooters should be dependent on whether or not there are strong public transportation options in the census tract area. The variables of "Rides by Area" and "Transit Index Score" were compared under a Pearson correlation to uncover any potential strong linear relationship, and then t-tests were performed to test if the means of e-scooter rides were different between transit deserts and transit oases.

Table 1. T-Tests Between Rides by Area and Transit Index Score

City	T-value	Degree of freedom	P-value	Mean number of rides by area	Mean of transit index score	Product-moment correlation
Austin	7.150	223	0.000	42.133	0.351	−0.432
Chicago	5.229	198.05	0.000	37.462	−1.321	−0.168
Minneapolis	4.088	150	0.000	78.511	0.674	0.317
Portland	−3.770	129	0.000	31.206	−0.203	−0.315

To accommodate for the census tract size discrepancies, the number of rides was divided by the acreage of the census tract. The area of the census tract was calculated in ArcGIS Pro and then modified by creating a new attribute; the number of rides was divided by the area of the census tract to create the new column of "Rides by Area." The resulting table was then exported as a CSV for further evaluation in RStudio. The unit of measurement for the census tract area was selected as acreage to ensure the resulting e-scooter ride number would be larger than one. This evaluation was performed while also preventing extreme outliers when the number of e-scooters was large or the census tract area was small. This phenomenon was discovered to happen frequently when the Shape Area was measured in cubic meters.

The transit index score was then joined by the census tract GEOID as illustrated in Figure 2. The transit index score was collected through the Urban Information Lab's ArcGIS online data portal (*21*). The transit index consists of measuring the transit supply (which is calculated by the number of transit routes and stops in a census tract), the street intersection density, and point of interest density. The transit demand consists of residents over 12 who are not institutionalized, according to the American Community Survey (*22*). The resulting data table could be reimported into ArcGIS for a basic visualization of e-scooter rides and transit deserts, and any visual relationship can then be confirmed through another data analysis software like RStudio.

Results

To predict the e-scooter rides for each census tract, we proposed a random forest model using the socioeconomic and health-related variables listed in Appendix Table 2. We analyzed the socioeconomic factors to reveal whether the transit score is a better predictor than other common sociological predictors.

Moreover, since e-scooters are a mode of transportation dealing with individuals' physical attributes, it is critical to include the health factors that correspond to limited mobility, such as arthritis and obesity. Appendix Table 2 represents the full description of the variable used in the random forest models. The random forest model of each city was run accordingly through RStudio using the "randomForest" program package. Furthermore, all the cities' data was merged into one data set to identify the best predictor of all the data (Figure 6).

The data for each city was tested for a linear correlation between the "Rides by Area" variable and the "Transit Desert Index" variable. The data appears to be non-linear for the cities with a change in the relationship between a transit desert and a transit oasis (Table 1 and Figure 3). Other correlations were displayed with a linear best-fit line, and it was discovered that a majority of the data fits with a hyperbolic curve better than with a linear curve (Figure 4). The vertex on Figure 4 was discovered to be around the zero axis of the transit index score, so each city was broken into the transit desert or transit oasis categories where an individual correlation could take place (Table 2).

A t-test was performed between the transit desert and transit oasis of each city to determine if there is a significant difference in the e-scooter rides between the two transit categories. The classification of a census tract being a transit desert is when the transit index is greater than zero (Table 3).

Discussion

The random forest algorithm model was used to try to predict the e-scooter rides by area. Specifically, this model type was chosen because the model is a classification and regression algorithm; additionally, the model benefits from the inclusion of multiple decision trees. A decision tree is an algorithm that can be used to solve both regressions and classifications. This allows for a decision tree to be generated as a training set that can predict the value of the recipient variable, in this case, the e-scooter trips. In a random tree classifier, every decision tree tries to forecast a response for an occurrence. The random forest creates multiple decision trees in a model, allowing each data point to be classified based on its attributes. The algorithm then "votes" on the tree based on the importance score and takes the average difference of all the trees that it combines to create the most accurate result. The variable importance is measured in two ways. The first step is permuting the data for each tree

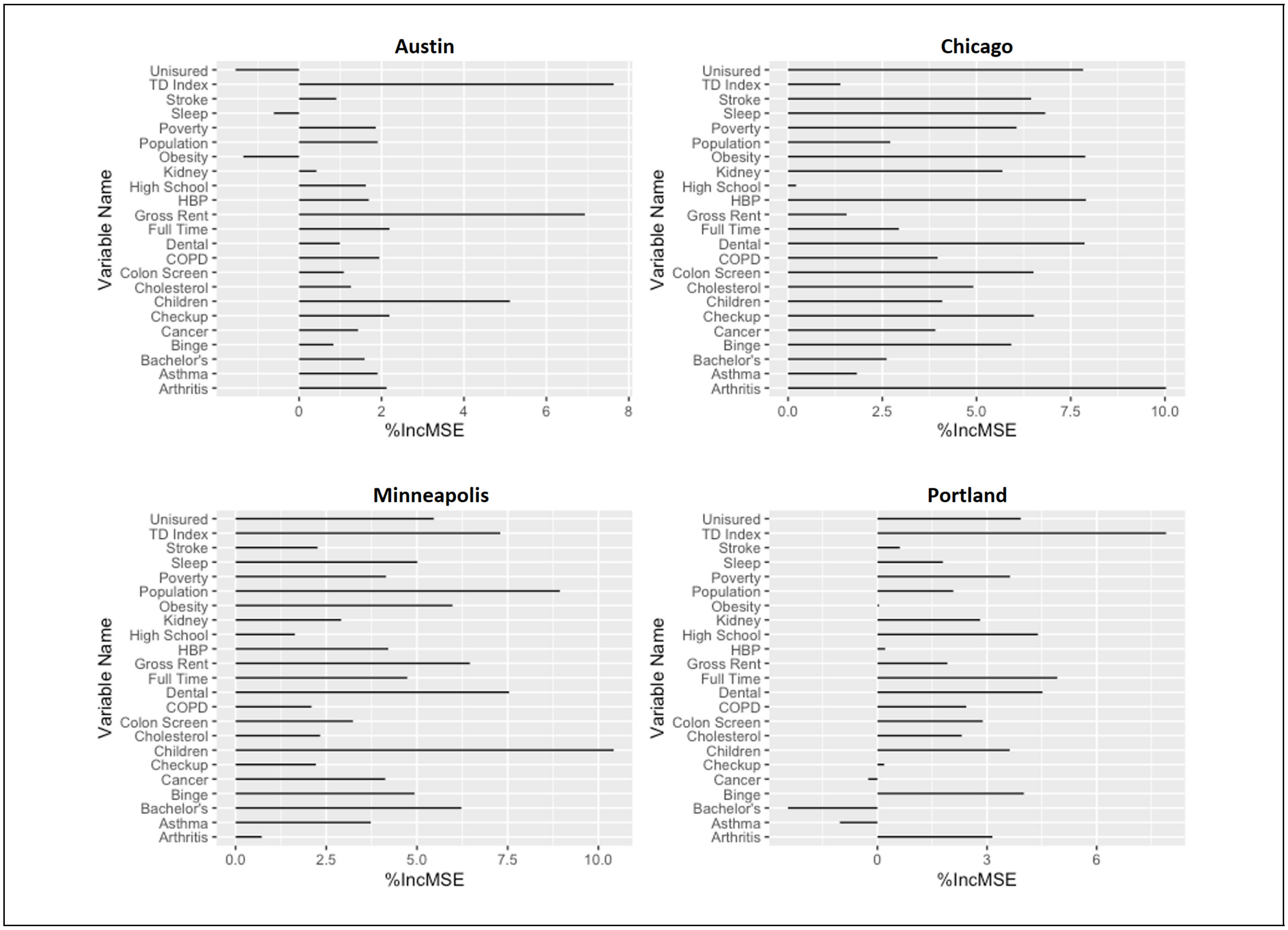

Figure 3. %IncMSE from random forest results of Austin, Chicago, Minneapolis, and Portland.

for each variable to create a prediction error, the mean squared error (MSE) for regression. Second, the measure of importance is calculated by the total decrease in the node impurities from splitting on the variable, which is averaged over all trees. In the regression process, this result is then measured by the residual sum of squares. Lastly, the %IncMSE is the increase in the MSE as a result of a variable being randomly shuffled. The higher the %IncMSE number is, the more significant the variable with regard to a relationship with the dependent variable, which would here be the number of e-scooter rides. The IncNodePurity shows the amount of function loss when the best split occurs. Typically, in random forests, the more valuable variables increase the node purities because the algorithm will have a harder time finding a split with both a high inter-node variance and small intra-node variance. The IncNodePurity scores are typically biased and would be viewed as only a basic reference point when determining which variable helps the prediction of e-scooter riders. The highest IncNodePurity for the combined cities is gross rent. However, it is important to note that %IncMSE has similar top variables, with gross rent being second. Therefore, the e-scooter rides are being heavily factored in the equations for gross rent and transit deserts. Adding many health factors to the algorithm was useful for the prediction process (as certain health factors should contribute to a person's mobility) and identification of better predictors for e-scooter trips. For example, people with arthritis would have more difficulties moving around the city than ordinary citizens. Suppose numerous health factors are a better predictor than the transit desert index score, it could then be possible to state that the e-scooter rides are independent of the transit supply.

The city of Austin's best predictor was the transit desert index (Figure 3). When referring to the correlation tests of Austin, the census tract's increase in transit desert index score evidenced that as it becomes more of a transit desert, the number of e-scooter rides increases. In addition, when the transit desert index decreases, the area thereby becoming a transit oasis, the number of e-scooter rides also increases. The number of e-scooter rides is

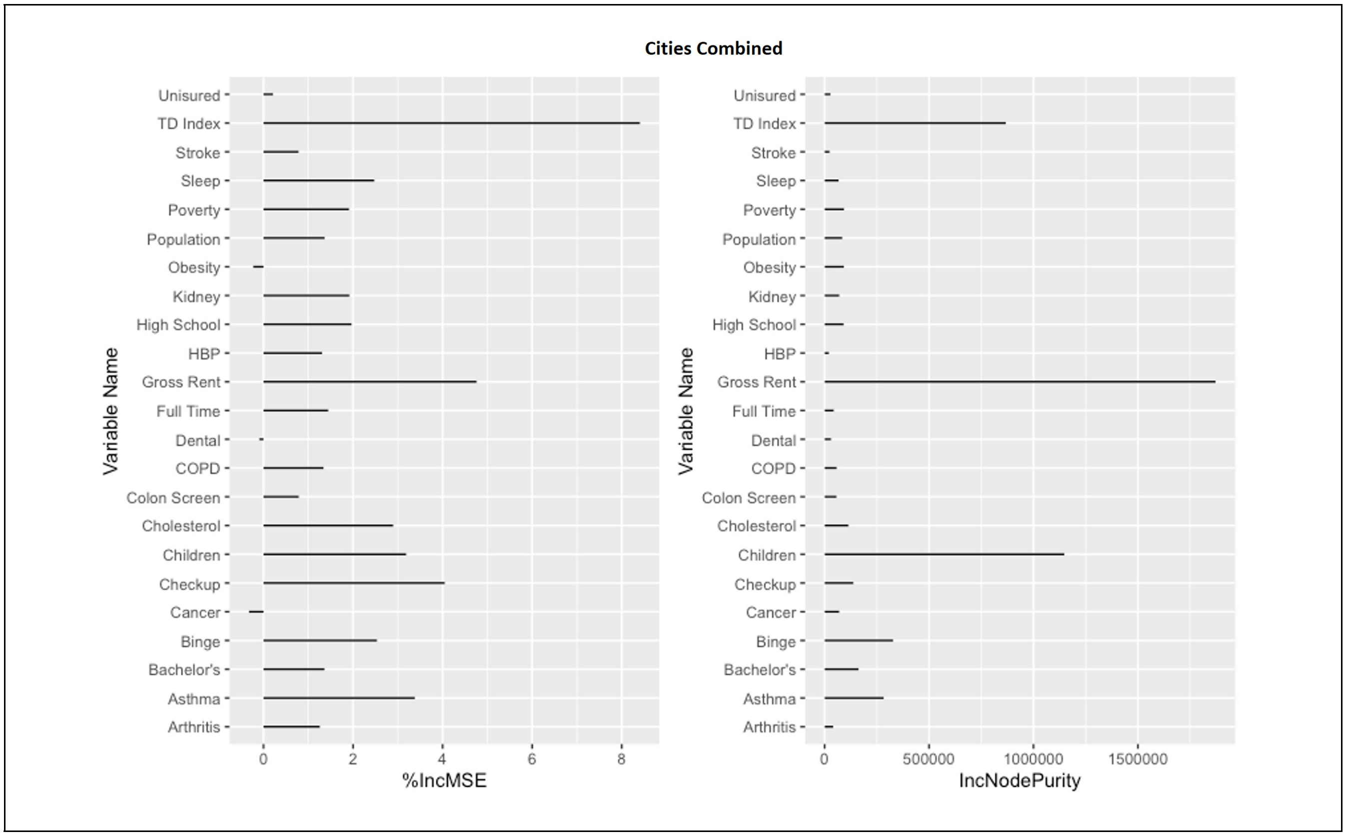

Figure 4. %IncMSE and IncNodePurity of random forest results for all cities combined.

Table 2. T-Tests Between Rides by Area and Transit Index Score Categorized by Transit Desert or Transit Oasis

City	T-value	Degree of freedom	P-value	Mean number of rides per area	Mean of transit index score	Product-moment correlation
Austin—Desert	2.255	155.01	0.025	27.236	0.637	0.793
Austin—Oasis	1.717	68.003	0.090	63.503	−0.744	−0.286
Chicago—Desert	2.132	19.004	0.046	28.550	0.499	0.031
Chicago—Oasis	4.925	178.03	0.000	38.458	−1.524	−0.185
Minneapolis—Desert	16.540	91.158	0.000	85.470	1.362	0.392
Minneapolis—Oasis	11.111	59.004	0.000	67.842	−0.381	−0.400
Portland—Desert	6.744	55.001	0.000	20.982	0.670	−0.164
Portland—Oasis	8.239	74.000	0.000	39.760	−0.855	−0.195

Table 3. T-Tests of Rides by Area in Regards of Transit Desert

City	T-value	Degree of freedom	P-value	Mean number of rides per area in transit oases	Mean number of rides per area in transit deserts
Austin	0.682	151.130	0.496	60.851	36.650
Chicago	0.882	108.590	0.378	16.390	10.773
Minneapolis	−2.212	0.029	0.029	67.842	85.470
Portland	1.924	44.181	0.061	42.978	26.779

usually at a minimum when the tract is not a transit desert or transit oasis. This is called transit adequate, meaning the transit desert index value is close to 0. In transit adequate zones, the supply and demand of transit are at close to equal levels. This meets the needs of the public on most days while sometimes underperforming or overperforming based on unique conditions. For example, a rare sporting event in the city might cause the transit demand to increase dramatically so that once adequate transit areas would temporarily become transit deserts.

According to the random forest model, the better predictor of e-scooter rides for Chicago is the arthritis crude prevalence estimate (Figure 3). When running a linear correlation, the comparison between "Arthritis" and "Rides by Area" variables produces a correlation of −0.177, which is slightly stronger than the correlation of the transit index to the "Rides by Area," which was −0.168. In the model using the adults with arthritis numbers, the census tract having a high number of arthritis citizens indicates a decrease in the number of e-scooter rides. Furthermore, if e-scooters were helping create new transit supply, it should also be increasing randomly in all areas of a city. There could be a component within the transit index that strongly coordinates to the rides of e-scooters. Furthermore, other studies might want to investigate the walkability index rather than transit deserts for the relationship with e-scooters. A possible explanation is that micro-mobility devices can only be used in locations with sidewalks, bike lanes, or low-traffic roadways.

Next, the random forest model in Figure 3 claims that the best predictor of e-scooter rides for Minneapolis is the number of households with children. The second-best predictor of Minneapolis was the crude prevalence of the population. In addition, Minneapolis had the transit desert index score as the third-best predictor. The other cities in this research have an increased ridership when the census tract is a transit desert or a transit oasis, and they have less ridership when the census tract is transit adequate (transit desert index $\approx$ 0). However, Minneapolis is the polar opposite, with lower ridership when a census tract is an extreme transit desert or transit oasis (yet more ridership when the census tract is transit adequate).

As shown in Figure 3, Portland's top predictor is the transit desert index. Also, full-time employment status seems to predict the number of e-scooter trips better than the other variables. However, a negative correlation appears when a linear regression is run between e-scooter rides and full-time employment status. The census tracts in the Portland city limits with high full-time employment status would then have lower e-scooter rides. The transit index score, the best predictor, displays a similar hyperbolic correlation with fewer scooter rides happening when the census tract is transit adequate (Figure 6). The random forest results show that the transit desert index is a decent predictor for the number of e-scooter trips. The next steps require determining the specific relationship between the transit desert index and the number of e-scooter rides.

The results of the t-test in Table 1 demonstrate that the means of both groups are different and could be independent given the p-value of the cities being low enough (less than 0.05) to be considered significant. Figure 5 and Table 1 show a positive correlation between the transit index and number of rides by area for Minneapolis. The corresponding linear relationship is found to be negative for Austin, Chicago, and Portland. It is important to note that increasing the transit index would mean the census tract is a transit desert. Therefore, the positive correlation implies that the areas with a lesser degree of accessibility to transit services (areas with a higher transit desert index value) are more likely to have a higher number of e-scooter rides normalized in the area. On the other hand, negative correlation would mean that areas with higher accessibility to transit services (areas with lower transit scores) tend to have a higher number of e-scooter rides divided by area. There are two main reasons for this correlation. First, travel behaviors and distribution of the population might differ from one city to another. Second, people living in transit deserts and oases might use e-scooters for different trip purposes. The data was visualized on a scatter plot to visualize the correlation further. The correlation was tried with different non-linear correlations to see if the relationship is non-linear.

In Figure 5, a non-linear relationship between the "Rides by Area" and "Transit Index Score" was discovered. Figure 6 was created with a parabolic curve, which fit the data better than a linear line. The investigation of Figure 6 revealed that the vertex of the curve appears to be around zero for the transit index score. This resulted in each city being divided into its transit desert and transit oasis counterparts. When the census tract's transit index score is greater than 0, the census tract is classified as a transit desert, and when the tract is less than 0, it is classified as a transit oasis.

Furthermore, the division of each city allows for two linear regressions to be run for each city. The results in Table 2 show that Austin, Chicago, and Portland have a negative correlation between transit index and e-scooter rides when the census tract is classified as a transit oasis. In this scenario, the census tract starts to have a positive correlation between the transit index and e-scooter rides when the census tract is classified as a transit desert. Minneapolis has the opposite result with census tracts that are transit deserts, resulting in a negative correlation between transit index and e-scooter rides. Consequently, it also maintains a positive correlation between the transit index and e-scooter rides when the census tract is a

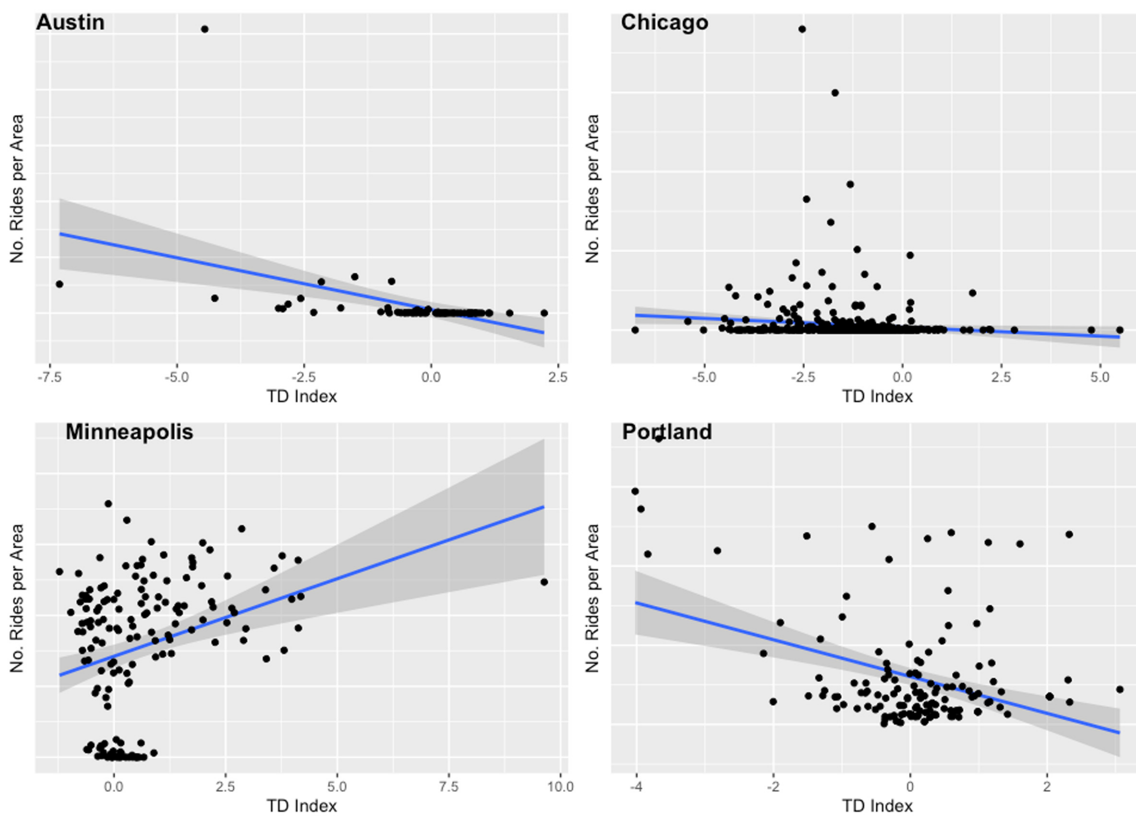

Figure 5. Graphical visualization of "no. rides per area" and the "transit desert (TD) index" for each city with a linear best-fit line.

transit oasis. Overall, when a census tract is on the extreme ends of the transit desert index, meaning that their transit desert index number was closer to -1 or $+1$, they showed a greater number of e-scooter rides compared with census tracts that are classed as transit adequate (TD Index $\approx$ 0).

As displayed in Table 1, each city individually exhibited a negative linear correlation, except for Minneapolis. When the four cities are combined, the chart displays a slight positive correlation of e-scooter rides. This connection might be a result of Minneapolis having a strong positive correlation and being able to shift the addition of the other points to a more positive correlation. As noted, when a city's census tract is on the extreme scales of being a transit desert or transit oasis, an increase in the number of e-scooter rides is then observed.

By answering where e-scooters are more likely to occur, it could be speculated that their occurrence is helping to add a layer of public transportation that could not have been initially provided from traditional forms of transportation. The wealthy neighborhoods in dense urban settings might have the luxury of personal vehicle transportation, while lower income neighborhoods may need to rely on public transportation. Furthermore, wealthier neighborhoods are in the less dense parts of the city as each person there occupies more space and requires space for a car. Access to a car allows a person to have higher job security (thanks to having stable transportation to work). Conversely, a person who relies on public transportation could be one train ride away from being late to their job, risking termination.

The 2019 e-scooter report by Portland Bureau of Transportation (*25*) in Oregon states that e-scooters were most used in heavily traveled areas, including "NE Going Street, SE 122nd Avenue, NW Johnson, SW Naito Parkway, and the Willamette Greenway Trail." These heavily trafficked areas are also a part of Portland's bikeway network, which might correspond to e-scooter rides happening more for leisure than for commuting in areas with a lack of public transportation. If e-scooters are being used more for leisure activities, it could explain why the e-scooter rides are happening in both extreme transit deserts and transit oases. Most leisure activities have a high density of people seeking transportation to a certain spot. For example, a park might have a bus station at the north end but be completely vacant of transportation at the park's southern end. The e-scooter rides could happen in both park areas

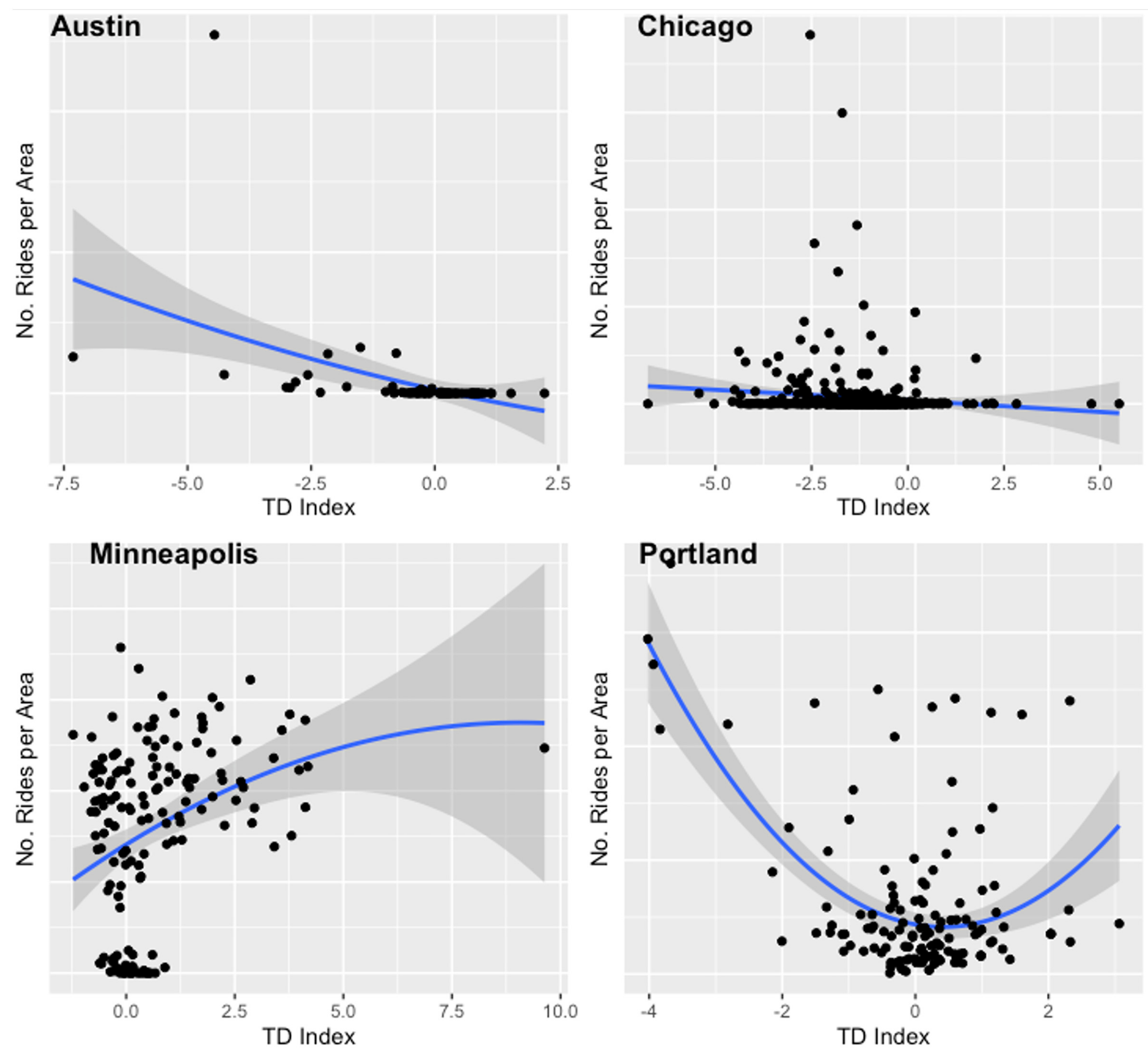

Figure 6. Graphical visualization of "no. rides per area" and the "transit desert (TD) index" for each city with a quadratic best-fit line.

but be occupied in two different types of transit indices. This theory may be supported by Appendix Table 2, where Minneapolis and Portland significantly differ in the mean of scooter rides between transit deserts and transit oases.

Cities could use the results of e-scooter analyses to take steps to solve issues like overcrowding on sidewalks and public areas caused by dockless e-scooters. For example, cities can create zones to limit the number of e-scooter deployments. If the cities do not allocate the e-scooters properly, this situation could cause the creation of new transit desert zones. The results show how a majority of cities have a certain relationship with the transit desert index. Therefore, it would be useful for cities to focus on addressing their transit deserts. Furthermore, cities should consider special events where micro-mobility would be especially popular. Regulators should be able to create flexible restrictions that change depending on the circumstances. Particular points of interest like tourist attractions might need to be given special circumstances to help provide the necessary amount, and local transportation experts should use the transit desert index to create the guidelines on the restrictions of e-scooters.

Conclusion

The selected cities of Austin, Chicago, Minneapolis, and Portland have displayed a strong correlation between the transit desert index score and e-scooter rides. Typically, when a census tract becomes more of a transit desert or transit oasis, the e-scooter count increases. The exception is in Minneapolis: when that city's census tract becomes more of a transit desert or transit oasis, the e-scooter rides were observed to decrease. The mean of e-scooter trips between the transit desert and transit oasis showed no significant difference in Austin, Chicago, or Portland. Minneapolis showed a significant difference in the mean of e-scooter rides between census tracts classified as transit deserts versus census tracts that are transit oases.

Furthermore, a greater number of e-scooter rides took place in census tracts classified as transit deserts. For Minneapolis, the mean of e-scooter rides in transit oases was 67.841, and the mean of e-scooter rides in transit deserts was 85.469. The e-scooter data was joined with corresponding CDC health demographics per the census tract. A random forest model was created for each city to try to predict the number of e-scooter rides. The best predictor for Austin and Portland was the transit desert index score, while Chicago's was the crude prevalence of arthritis among adults aged $\geqslant 18$ years, and in Minneapolis it was the crude prevalence of households with children. However, the transit index score placed first for Austin, 13th for Chicago, fourth for Minneapolis, and third for Portland. Last, the transit desert index score was the best predictor for e-scooter rides when the cities were combined as in Figure 4.

Many cities are placing limits on where e-scooters can be deployed (*26*). E-scooters might be helping to increase the supply of transportation, but if the e-scooters are not used effectively, they will be useless. The allocation of e-scooters based on population or heavily trafficked areas might not be the best way. If cities are trying to predict the number of e-scooter rides per census tract, the recommendation based on this study would be to use the transit desert index score highlighted in the methods, given the high predictive nature of the results from the random forest models. Furthermore, the high predictive nature of the transit desert index score for the number of e-scooter rides could be used by e-scooter companies to place e-scooters where citizens tend to use e-scooters more frequently. These locations tend to be in regions on the extreme ends of the transit desert index scale. The census tracts with adequate transportation (transit index $\approx$ 0) tended to have a lower number of e-scooter rides than the census tracts that were distinctly a transit desert or transit oasis. It is important to note that spatial planning in the cities would account for the clusters of e-scooter rides. A future research analysis could evaluate the specific trip-types to identify patterns in users' end destinations. The first limitations of the study are that most cities do not provide the same level of access to data. For example, Austin includes data for an entire year, while Minneapolis provides a few select months. In addition, some other e-scooter data for select cities are only available for authorized users. If the research was to be expanded on, access to more cities' e-scooter data and a longer time frame for the data would help the analysis. In addition, if possible, a smaller scale beside the census tract would allow for the results to be even more precise. Similarly, scaling the study to a higher scale, such as the the zip code level, would provide a larger general representation of e-scooters but would lose the precision of smaller-scale research.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: N. Degen; data collection: N. Degen; analysis and interpretation of results: N. Degen; draft manuscript preparation: N. Degen, A. Azimian, and J. Jiao. All authors reviewed the results and approved the final version of the manuscript.

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Supplemental Material

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