Transportation Research Part A 149 (2021) 114–123

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Scootin' in the rain: Does weather affect micromobility?

Robert B. Noland

Alan M. Voorhees Transportation Center, Edward J. Bloustein School of Planning and Public, Policy Rutgers University, New Brunswick, NJ 08901, United States

ARTICLE INFO

Keywords:
Shared e-scooters
E-bikes
Docked bikeshare
Weather

ABSTRACT

The usage of shared e-scooters, dockless e-bikes, and docked bicycles are correlated with weather conditions to examine the relative impact on each mode, specifically number of trips taken, their duration, and distance. Data is obtained from the City of Austin data portal. Rain, temperature and wind conditions are obtained from NOAA and a variety of analysis methods are applied, specifically Prais-Winsten and Negative Binomial regressions as well as a Random Forest model to examine the full suite of weather variables and to avoid some of the distributional issues in the trip models. In addition, controls are included for holidays, days of the week, and special events in Austin (such as the SXSW festival); all are found to be critical control variables, with SXSW associated with large increases in trips. Results suggest that docked bicycle and e-bike usage is more sensitive to adverse weather conditions than e-scooter trips, though all are reduced in colder, rainier, and windier conditions, as well as extreme heat and high relative humidity.

1. Introduction

Micromobility options, such as shared e-scooters, e-bikes and bicycles are able to provide increased travel options for short trips. However, these modes are also sensitive to weather conditions, potentially limiting their usefulness at certain times of the year, especially in wetter and colder conditions. In this work, I examine one year's worth of shared e-scooter, dockless shared e-bikes, and docked bikeshare data from Austin, Texas, and correlate usage with weather conditions, namely temperature, relative humidity, precipitation and wind speed. Results focus on a comparison between the three modes and overall impacts of weather on the number of trips taken, their duration and the length of trips.

These micromobility modes are seen by some planners as a potential alternative to car travel within cities. They are also seen as offering access and egress from transit as a "last mile" option. However, if weather conditions have an adverse impact on these new modes, it might not be possible to view them as complete substitutes. There is certainly ample evidence that bicycle use is much lower in bad weather. E-scooters, on the other hand, may be less sensitive to weather conditions, perhaps due to needing less physical effort or because most trips are much shorter. My primary hypothesis is that bicycles (including e-bikes) are more sensitive to weather conditions than e-scooters. If this is the case, e-scooters could be more resilient to adverse weather than bicycles and a more useful option for reducing vehicle use in cities.

The physical exertion needed to bicycle and to use an e-bike may reduce their use during extreme heat. E-scooters require less exertion so may be less affected in these conditions. E-scooters also may allow the user to wear better all-weather clothing to avoid getting soaked in rainy conditions. Trips on e-scooters also tend to be shorter, so are less affected by cold temperatures. Thus, while I cannot identify user motivations in this work, the data available allows one to observe actual daily usage of each mode and link this to

E-mail address: rnoland@rutgers.edu.

https://doi.org/10.1016/j.tra.2021.05.003
Received 19 August 2020; Received in revised form 17 February 2021; Accepted 10 May 2021
Available online 21 May 2021
0965-8564/

daily weather conditions.

A few studies have previously examined e-scooters and weather impacts. The first was a small study of usage in Louisville, Kentucky (Noland, 2019). This study correlated daily usage with weather conditions. Findings suggested that while rain and snow reduced usage, changes in average temperature and wind speed had no effect on total daily trips. However, distances traveled were lower when windy and increased with warmer temperatures. Speeds likewise increased with warmer temperatures. Patterns of usage in Louisville suggest that e-scooters are primarily used for recreation. This prior analysis was also limited as the data available did not cover a full year of usage. Two other recent studies examined e-scooters and weather, both finding similar effects. One used data from Indianapolis, Indiana (Mathew et al., 2019) while the other used data from Washington, DC (Younes et al., 2020); this latter study also compared e-scooters with docked bikeshare usage, finding that e-scooters were less sensitive to weather conditions. None of these prior studies adequately controlled for serial correlation in the data, something that I do in this analysis; despite this shortcoming, results are generally similar. A survey based study, conducted in Tempe, AZ, found that respondents preferred e-scooters to walking in hot weather (Sanders et al., 2020).

Weather conditions undeniably affect bicycle trips and to some extent it is obvious that recreational cycling would decrease in adverse weather. Bicycle commuters, some of who may have limited alternative modes, are also likely to be affected. Data collected on bicycle commuters in Vermont, which tends to have very cold winters, confirmed that rain and snow reduced the likelihood of commuting by bicycle (Sears et al., 2012). As morning temperatures increased there was an increase in commuting of about 3% per 1 °F (0.56 °C) increase in temperature, covering a range from −3.2 °F to 79.2 °F (−19.5 °C to 26.2 °C). Increased wind speeds also decreased bicycle commuting. In another study that analyzed a northern city, Toronto, Canada, findings showed that bicyclists are sensitive to temperatures below 15 °C (59 °F), as well as to precipitation and wind (Saneinejad et al., 2012). A study in a more temperate climate (Melbourne, Australia) of student cyclists reported that adverse weather conditions affects cycling (Nankervis, 1999).

The studies cited above all rely on reported data or observations. Bike-sharing data allows actual usage to be examined and various studies confirm the reduction in bicycle usage with adverse weather. Gebhart and Noland (2014) examined data from the bikeshare system in Washington, DC, correlating usage at one-hour intervals with weather conditions. Findings were unsurprising and showed that precipitation, cold temperatures, wind, and high humidity levels reduced the number of trips. Kim (2018) analyzed data from bike-sharing in Daejeon, South Korea, finding similar effects. His study controlled for humidity levels and found that high temperatures (above 30 °C) led to fewer trips. A study using bike-share data from Brisbane, Australia (a semi-tropical climate) found less variation in trips due to weather; similar effects to other studies were found for rain and wind (Corcoran et al., 2014).

Both Kim (2018) and Corcoran et al. (2014) controlled for weekends and holidays in analyzing bikeshare trips. In my analysis I control for weekends, holidays, the university school session as well as special events in Austin (the SXSW festival and university football games) which attract large numbers of visitors. These controls are important to include, as my findings will demonstrate. The main focus of the analysis that follows is on comparing impacts of weather for shared e-scooters, e-bikes and docked bikeshare, however, the effect of special events is also an important finding.

1.1. Data

Data on all dockless modes is limited as these systems are run by private companies that do not typically make their data available. The City of Austin, Texas, however provides these data via their open data portal (City of Austin, 2019). This dataset is updated continually and includes every trip taken by shared e-scooters and shared dockless e-bikes since April 2018.[1] Over 7 million records, i.e., one for each trip, were downloaded on Oct 18th, 2019. Of these, about 6.2 million were trips taken between Oct 1st, 2018 and Sept 30th, 2019. This covers the period when about seven e-scooter and bikeshare companies were operating in the city. Additional data cleaning led to a final dataset of 5,757,701 trips as detailed in Table 1 (about 92% of the total data). Most of those removed had a recorded distance of zero.

The docked bikeshare (i.e., regular pedal bicycles) is run by B-cycle (https://austin.bcycle.com/). This data is also available on the open data portal and was downloaded on Aug 13th, 2020. Over 1.2 million trips had been taken since inception of the system in 2014, with 150,780 records recorded between Oct 1st, 2018 and Sept 30th, 2019. A small fraction had a recorded distance of zero and were removed from the data, leaving 149,273 records (see Table 1).

Of the dockless trips, some 94.5% (5,441,174) were e-scooter trips and 5.5% (316,527) were e-bike trips. This comes to an average of 14,907 e-scooter trips per day and 874 e-bike trips per day. Docked bikeshare trips, on average, were only 409 per day. The average duration and distance of trips for all modes is shown in Table 2. Not surprisingly, e-scooter trips are shorter than e-bicycle trips in both duration and distance, while docked bikeshare trips have the longest duration (distance data was not available); this may be partly due to the relatively higher cost of e-scooter and e-bike rentals, compared to the docked bikeshare.

The data was aggregated by day to analyze total trips and mean duration and distance by day. While e-scooter data was available for every day, I found two days in which the dockless e-bicycles were not used, June 29th and 30th, 2018; in addition the data was not available for about half of June 28th. This seems to have been a system shutdown or malfunction, but I have no specific information on the cause. I removed these days from the e-bicycle data.

[1] The data only distinguishes between scooters and bicycles. Currently, all the bicycles are e-bikes, but a small share in the data may be regular bicycles. A small share of the scooters include sit-down scooters, but the majority are standing scooters. Current services are listed here (though not corresponding to when the data for this study was downloaded): http://austintexas.gov/department/shared-mobility-services

Table 1
Data downloaded from City of Austin (2019) and process of cleaning data.

	Number of dockless records	Number of docked bikeshare records
Total trips downloaded	7,543,305	1,216,805
Deleted trips before 10/1/18	996,796	1,067,532
Deleted trips after 9/30/19	324,801	NA
Total records, 10/1/18 to 9/30/19	6,221,708	150,780
Deleted if distance > 80 km	2308	–
Deleted if distance <= 0	449,792	–
Deleted if duration > 12 hrs	282	0
Deleted if duration <= 0 hrs	407	1507
Deleted if speed > 50 km/hr	11,217	–
Deleted empty records	1	–
Final number of records (trip count)	5,757,701	149,273

Note: dockless files contain e-scooters and e-bikes and was downloaded on 10/18/19; docked bikeshare files were downloaded on 8/13/2020; for docked bikeshare duration data was available and trip data was available from 2014 up to 9/30/2019.

Table 2
Average daily distance and duration of e-scooter and bicycle trips, Oct 1, 2018 to Sept. 30, 2019.

	Average duration (mins)	Average distance (meters)
E-scooter trips (N = 365)	10.8	1493
E-Bicycle trips (N = 362)	16.7	2614
Docked Bikeshare trips (N = 365)	48.7	NA

Trip counts by day for e-scooters, dockless e-bicycles, and docked bikeshare are shown in Fig. 1, Fig. 2, and Fig. 3, respectively. Various patterns stand out in these line graphs. First, there is a large peak in March 2018 with over 50,000 daily e-scooter trips and 4000 daily dockless e-bicycle trips occurring. This corresponds with a large event in Austin, the South by Southwest (SXSW) festival which attracts participants from the technology industry. There is a smaller peak at this time for the docked bikeshare trips. Another smaller peak occurs, for e-scooters and e-bikes in early September corresponding to the start of classes at the University of Texas which is located in the center of Austin. The docked bikeshare usage also shows a large decline, with far fewer trips in the Summer of 2019 compared to the Fall of 2018. This may be due to the popularity of the e-scooters compared to the docked bikeshare. Seasonal effects are also apparent, especially for e-bicycle trips which drop off from about December through February. There is also variation between days of the week, with Saturdays being the peak usage day for all modes (see Table 3), though the variation is less for docked bikeshare trips.

Given the variation between days of the week, I control for this in the regression analysis. I also include a dummy variable for the days of the SXSW festival (March 8th–17th, 2019). Dummy variables are also included for days when the University of Texas is in session (Aug 23rd 2018–Nov 20th, 2018; Nov 25th, 2018–Dec 20th, 2018; Jan 22nd, 2019–March 15th, 2019; March 20th, 2019–May 21st, 2019). Given the importance of football in Texas, I also included a dummy variable for home games at the University of Texas (Oct 13th, 2018; Nov 3rd, 2018, Nov 17th, 2018, Sept 7th, 2019, and Sept 21st, 2019). These days have substantially more trips by all three modes as shown in Table 4, including more trips on other Saturdays when football games do not take place. Table 4 also displays the number of trips on SXSW days, which far exceeds the average.

Data on daily weather patterns were downloaded from NOAA (2019). The closest weather station with a full set of data was Austin-Bergstrom airport. Data for average temperature, minimum and maximum temperature, amount of rain, relative humidity, and average wind speed were obtained. I also have two measures of gusty winds, WSF2 measuring the fastest 2-minute wind speed, and WSF5 measuring the fastest 5-second wind speed. Summary statistics are displayed in Table 5; as can be seen, Austin has a relatively mild climate, although summer conditions can be quite hot, with 129 days exceeding 80 °F (26.7 °C).[2]

2. Methods and analysis

My underlying hypothesis is that weather has a larger impact on bicycle trips than e-scooter trips. I investigate this by estimating models that associate the daily number of trips with daily weather conditions over an entire year. I control for day of the week, holidays, the University of Texas school session, football games and the SXSW festival. I also estimate average trip duration and distance using the same variables. I interpret results based on coefficient effect size and statistical significance.

Analysis of daily trips is complicated by the fact that trips are counts. This calls for a Poisson or Negative Binomial regression rather than a standard ordinary least squares model. However, the data is also serially correlated and therefore a Prais-Winsten model is required to control for this. Negative Binomial models assume independence in each day and thus cannot control for serial correlation. Thus, I estimate a Prais-Winsten model, a Negative Binomial model, and then another Prais-Winsten model with the logarithm of the

[2] I use degrees Fahrenheit for my temperature units as this is how NOAA presents their data. Conversions to Celsius are provided in the text.

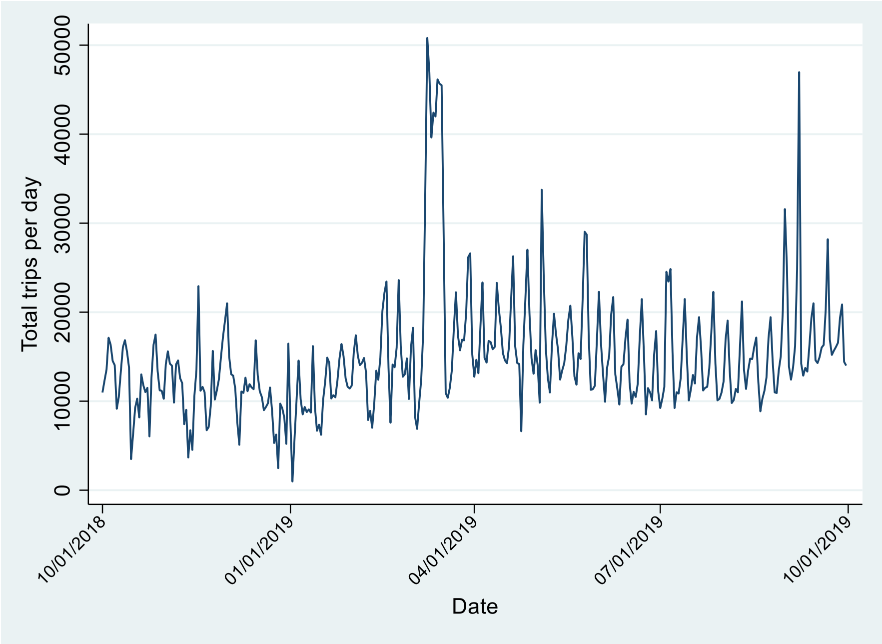

Fig. 1. Total daily e-scoooter trips, Oct 1, 2018 to Sept. 30, 2019.

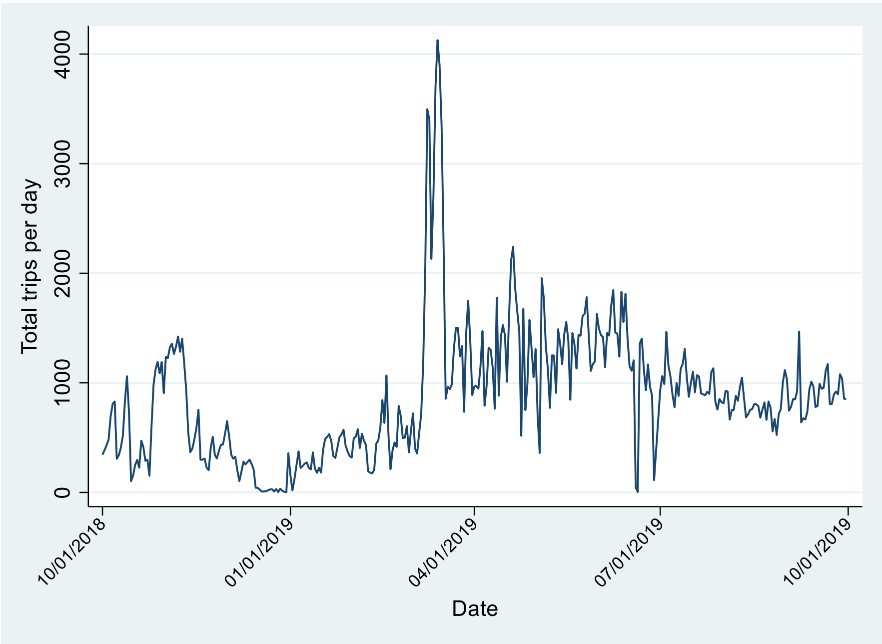

Fig. 2. Total daily dockless e-bicycle trips, Oct 1, 2018 to Sept. 30, 2019.

dependent variable, in order to better approximate a normal regression. However, this model still fails a Shapiro-Wilks test for normality. In addition, inclusion of all the weather variables was not possible due to multicollinearity, thus I only include average temperature, relative humidity, a dummy for temperatures at or above 80 °F (26.7 °C), average wind speed, and inches of rainfall.

It is clear looking at the Durbin-Watson test for these models in Table 6, Table 7, and Table 8 that there is a need to adjust for serial correlation. The adjusted-R^2 is relatively high in the e-scooter models and highest for the logged Prais-Winsten, suggesting this model has a good fit. Adjusted R^2 is lower for the e-bicycle and docked bikeshare models. Despite these distributional concerns, each model provides similar results for the relative effect and significance of most parameters.

In the e-scooter models (Table 6), most parameter estimates are similar for each model, though there are minor exceptions. Football

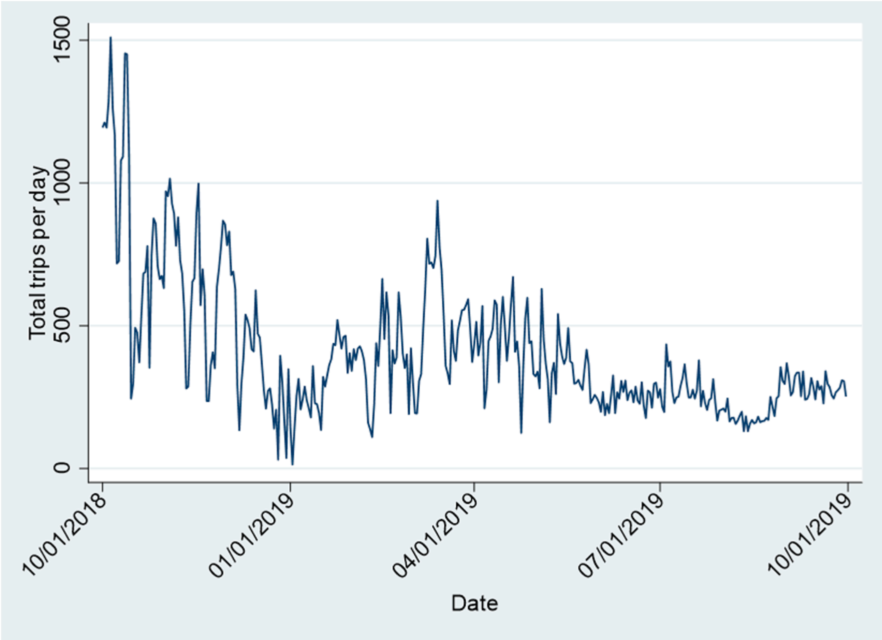

Fig. 3. Total daily docked bikeshare trips, Oct 1, 2018 to Sept. 30, 2019.

Table 3
Average e-scooter and bicycle trips by day of week, Oct 1, 2018 to Sept 30, 2019.

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Average e-scooter trips	15,382	12,047	12,148	12,300	14,221	17,295	21,014
Average e-bicycle trips	933	776	776	765	850	992	1035
Average docked bikeshare trips	398	398	384	370	415	446	452

Table 4
Average e-scooter and bicycle trips on days with and without football games and during SXSW.

	Football days	Other days	Other Saturdays	SXSW days
Average e-scooter trips	25,578	14,759	20,528	42,126
Average e-bicycle trips	1156	870	1021	3106
Average docked bikeshare trips	819	360	413	727

Table 5
Average weather, Austin-Bergstrom airport station, Oct 1st, 2018–Sept. 30th, 2019 (NOAA, 2019).

	Mean	Std. Dev.	Min	Max
Average daily temperature (°F)	68.80	14.71	35.00	89.00
Average daily minimum temperature (°F)	57.85	15.49	24.00	81.00
Average daily maximum temperature (°F)	80.13	15.78	40.00	102.00
Average daily rainfall (inches)	0.11	0.42	0.00	4.77
Average relative humidity (%)	69.72	11.35	35.00	94.00
Average daily wind speed (mph)	8.46	3.65	2.01	19.91
WSF2 (fastest 2-minute wind speed)	20.1	6.08	8.1	45
WSF5 (fastest 5-second wind speed)	25.9	7.87	10.1	66
Days above 80 °F	129			

days are not significant in the Negative Binomial model and relative humidity, while statistically significant, has a zero coefficient in the same model (i.e., very small, though not much different than the logged Prais-Winsten model).

The e-bicycle trip model has more variation in estimates (Table 7). The Prais-Winsten model with levels tends to have results suggesting more statistical significance, especially for some days of the week (Friday and weekends). Excessive temperature, i.e., at or above 80 °F (26.7 °C) is not consistently positive and signifcant for e-bikes and wind speed also differs between models, but other

Table 6
Daily e-scooter trip models.

	Prais-Winsten dep. var. = daily trips		Negative Binomial dep. var. = daily trips		Prais-Winsten dep. var. = ln(daily trips)	
	Coef.	t	Coef.	z	Coef.	t
Holiday	−515.84	−0.56	0.02	0.23	−0.03	−0.42
Tuesday	7.38	0.02	0.00	0.01	0.02	0.53
Wednesday	385.77	0.67	0.01	0.25	0.00	0.02
Thursday	**1960.29**	**3.20**	**0.15**	**3.44**	**0.16**	**3.76**
Friday	**5010.37**	**8.16**	**0.35**	**7.80**	**0.36**	**8.36**
Saturday	**7790.06**	**13.18**	**0.50**	**10.81**	**0.50**	**11.82**
Sunday	**2788.57**	**5.88**	**0.22**	**4.81**	**0.22**	**6.38**
School in session	**2370.18**	**3.62**	**0.21**	**7.66**	**0.20**	**4.62**
SXSW days	**21935.30**	**12.98**	**1.01**	**13.50**	**0.90**	**7.83**
Football days	**5757.82**	**4.65**	0.14	1.32	**0.19**	**2.14**
Average wind speed	**−155.04**	**−3.21**	−0.01	−1.93	**−0.01**	**−4.34**
Rain (inches)	**−2302.48**	**−6.56**	**−0.24**	**−8.49**	**−0.25**	**−9.69**
Average daily temperature (°F)	**156.57**	**6.46**	**0.02**	**11.03**	**0.01**	**8.14**
Relative humidity (%)	**−64.91**	**−3.88**	**0.00**	**−4.26**	**−0.01**	**−4.33**
At or above 80°F	**−1561.36**	**−2.21**	**−0.18**	**−3.95**	**−0.12**	**−2.43**
Constant	**6086.85**	**3.00**	**8.65**	**74.09**	**8.81**	**62.60**
Rho	0.54				0.49	
DW	1.10				1.11	
DW(final)	2.00				2.07	
Alpha			0.05			
N	365		365		365	
RMSE	2960.90				0.21 (3657.33)[b]	
Adj-R^2	0.63		0.06[a]		0.68	

Note: bolded values indicate at or above 95% level of statistical significance.
[a] Psuedo-R^2 for NB model.
[b] based on levels instead of log predictions.

Table 7
Daily e-bicycle trip models.

	Prais-Winsten dep. var. = daily trips		Negative Binomial dep. var. = daily trips		Prais-Winsten dep. var. = ln(daily trips)	
	Coef.	t	Coef.	z	Coef.	t
Holiday	15.84	0.22	−0.26	−1.24	−0.14	−0.96
Tuesday	0.77	0.02	−0.04	−0.33	0.00	−0.06
Wednesday	2.13	0.05	−0.08	−0.65	−0.13	−1.36
Thursday	62.54	1.24	0.02	0.16	−0.05	−0.47
Friday	**211.00**	**4.14**	0.18	1.39	**0.22**	**2.03**
Saturday	**191.39**	**3.99**	0.16	1.20	0.16	1.54
Sunday	**126.59**	**3.43**	0.10	0.80	0.09	1.14
School in session	14.13	0.16	0.11	1.32	−0.08	−0.45
SXSW days	**1100.78**	**5.90**	**1.26**	**6.03**	0.60	1.53
Football days	**291.76**	**3.10**	0.21	0.70	0.38	1.95
Average wind speed	−7.57	−1.93	0.01	0.59	**−0.02**	**−2.44**
Rain (inches)	**−173.44**	**−6.48**	**−0.27**	**−3.15**	**−0.31**	**−5.58**
Average daily temperature (°F)	**9.83**	**3.92**	**0.04**	**11.21**	**0.03**	**4.89**
Relative humidity (%)	**−4.29**	**−3.18**	**−0.01**	**−3.03**	**−0.01**	**−3.00**
At or above 80°F	−69.51	−1.08	**−0.58**	**−4.71**	−0.16	−1.15
Constant	**475.63**	**2.25**	**4.43**	**13.51**	**5.50**	**12.42**
Rho	0.83				0.83	
DW	0.68				0.48	
DW(final)	2.26				2.24	
Alpha			0.40			
N	362		362		362	
RMSE	256.52				0.54 (555.22)[b]	
Adj-R^2	0.31		0.03[a]		0.26	

Note: bolded values indicate at or above 95% level of statistical significance.
[a] Psuedo-R^2 for NB model.
[b] based on levels instead of log predictions.

Table 8
Daily docked bikeshare trip models.

	Prais-Winsten dep. var. = daily trips		Negative Binomial dep. var. = daily trips		Prais-Winsten dep. var. = ln(daily trips)	
	Coef.	t	Coef.	z	Coef.	t
Holiday	−0.27	−0.01	0.00	0.01	−0.02	−0.25
Tuesday	−15.34	−1.13	−0.08	−1.00	−0.06	−1.22
Wednesday	−18.97	−1.09	−0.09	−1.06	**−0.14**	**−2.31**
Thursday	11.14	0.58	0.05	0.64	0.00	0.04
Friday	**57.49**	**3.00**	0.14	1.77	0.10	1.63
Saturday	**41.73**	**2.32**	0.11	1.31	0.09	1.44
Sunday	5.62	0.41	−0.01	−0.17	−0.05	−0.97
School in session	69.99	1.94	**0.56**	**11.31**	**0.36**	**3.79**
SXSW days	116.25	1.59	**0.44**	**3.28**	0.34	1.55
Football days	**119.07**	**3.38**	**0.55**	**2.83**	0.16	1.33
Average wind speed	**−8.29**	**−5.59**	−0.01	−1.93	**−0.02**	**−4.42**
Rain (inches)	**−63.61**	**−6.38**	**−0.28**	**−5.39**	**−0.26**	**−7.52**
Average daily temperature (°F)	**4.96**	**4.99**	**0.01**	**3.73**	**0.01**	**3.73**
Relative humidity (%)	**−3.96**	**−7.79**	0.00	−0.46	**−0.01**	**−6.30**
At or above 80°F	−34.88	−1.48	**−0.45**	**−5.77**	**−0.23**	**−3.03**
Constant	**387.75**	**4.14**	**5.27**	**25.98**	**5.93**	**24.34**
Rho	0.91				0.75	
DW	0.35				0.70	
DW(final)	2.17				2.36	
Alpha			0.16			
N	365		365		365	
RMSE	99.70				0.32 (224.04)[b]	
Adj-R^2	0.38		0.05[a]		0.44	

[a] Psuedo-R^2 for NB model.
[b] based on levels instead of log predictions.

weather variables have consistent directional effects. For the docked bikeshare models there is similar variation between models, particulary for wind speed, relative humidity, and temperatures at or above 80 °F (26.7 °C).

To further examine these estimation complexities I employ a Random Forest model (Breiman, 2001). Random forests are an algorithmic model designed primarily for predictive statistics. However, they also can be used to evaluate the relative importance of variables in a predictive model. The added benefit is that they are free of distributional assumptions and can include a full set of correlated variables. Thus, I include all the weather variables listed in Table 5 in a Random Forest model. The rforest procedure in Stata was used (Schonlau, 2019), with 1000 iterations. Results are presented based on the importance of each parameter and the RMSE of the model (for comparison to the RMSE in the regression models).

Results from the Random Forest model are displayed graphically in Fig. 4. The days of the SXSW festival dominate in importance for both e-scooter and e-bicycle trips, but not for docked bikeshare trips. Football days and Saturdays are also important predictors of e-scooter usage and especially so for docked bikeshare; this may be because usage was still high during Fall 2018. The school session is an important predictor for docked bikeshare usage. The RMSE is improved over the regression models. All the weather variables are shown to be important in the docked bikeshare model.

To better examine the relative importance of all variables I estimate the Random Forest model without the SXSW days (for the e-scooter and e-bike trip models) and this result is shown graphically in Fig. 5. The RMSE improves further when SXSW days are omitted. Football days and Saturdays are still important predictors for e-scooter usage. Of note, however, the weather variables are all more important predictors of e-bicycle usage than for e-scooters, as were dockless bikeshare in the full model. Temperature variables tend to be more important for e-bikes and docked bikeshare than the wind variables (all of which are about the same in their level of importance). The differences between temperature and wind are less pronounced for e-scooters.

3. Results of trip generation models

Random Forest results do not indicate what the directional effect is, but the prior regressions suggest that higher temperatures increase usage of all three modes while rain, higher relative humidity and higher wind speeds reduce usage. The effect of excessive temperature above 80 °F (26.7 °C) is mixed, but generally suggests a decrease in use of all modes, with a consistent negative parameter in the e-scooter models.

But how do the modes compare? The key finding is that weather effects are more important in predicting e-bicycle use and docked bikeshare use than e-scooter use, based on the Random Forest results. Of the statistical models presented, the Prais-Winsten models, with a logged dependent variable are probably the most reliable. These show some greater sensitivity to weather for the bicycle modes, especially average wind speeds (coefficient doubles), rain (small increase in value), average temperature (increase for e-bikes), relative humidity (no difference in coefficient value), and excessive temperature above 80 °F (26.7 °C) (negative in all cases, not significant for e-bikes and largest value for docked bikeshare). Many of the coefficient values are small as are their differences.

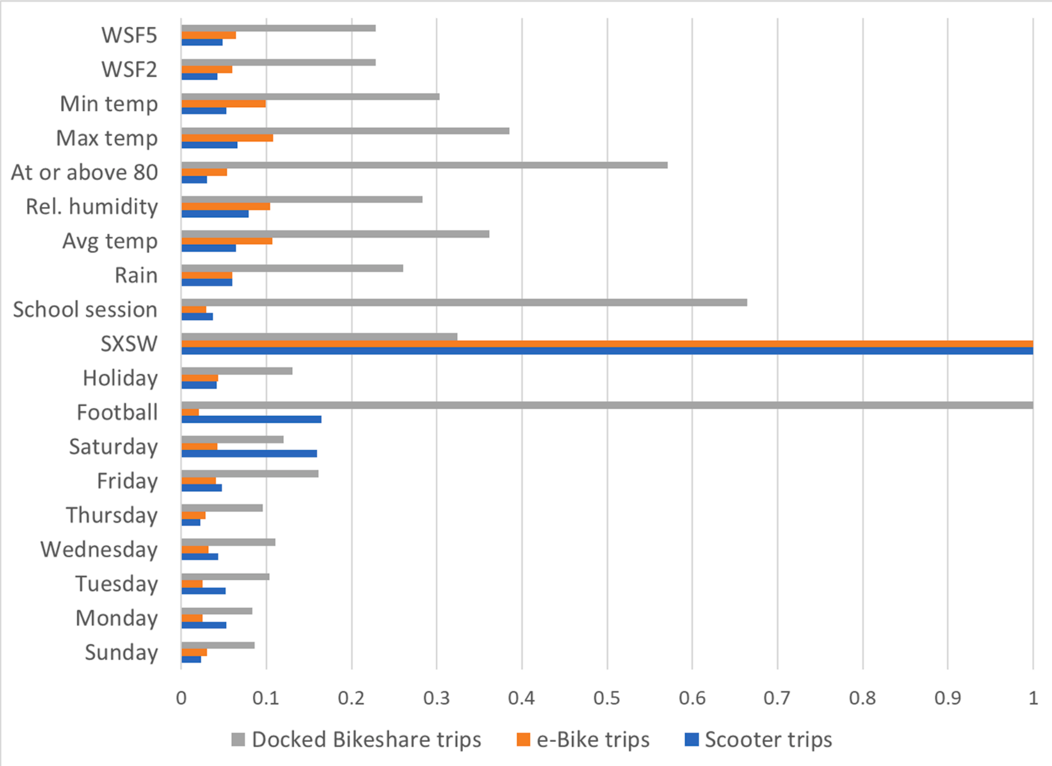

Fig. 4. Relative importance of parameters from Random Forest model, e-scooters, e-bikes, and docked bikeshare trips. Note: RMSE for e-scooter trip model: 1837.52; RMSE for bicycle trip model: 175.02; RMSE for docked bikeshare trip model: 75.04. Importance levels are normalized to 1 for the variable that has the largest predictive effect. N = 365 for daily scooter trips and docked bikeshare trips, N = 362 for daily e-bike trips.

4. Analysis of distance and duration of trips taken

Additional perspective on how weather affects micromobility usage can be gleaned from the distance and duration of trips taken. In Table 2, the average duration and distance is shown, though distance data was not available for docked bikeshare. On average bicycle users travel farther and for longer periods of time compared to e-scooter users. This may be due to the relatively higher per minute cost of using e-scooters especially compared to the docked bikeshare (which offers a subscription and 30 min pricing increments rather than by the minute). In Table 9, Prais-Winsten regressions are shown for both distance and duration of e-scooter and e-bicycle trips, and duration of docked bikeshare trips. These models account for serial correlation and as the dependent variable is not a count variable, further analysis is not needed.

Several patterns emerge from these models. First, the SXSW festival has no impact, i.e., trip distance and duration is no different on these days. Likewise for football days. However, Saturdays and Sundays are positive and statistically significant, implying increased trip distance and durations for all modes; e-scooters and e-bikes also have longer trips on holidays. On these non-work days, the coefficients in the e-bicycle models are larger than the e-scooter models, implying that distance and duration for e-bicycle trips on non-work days are longer than e-scooter trips. The coefficients for docked bikeshare are much lower, though positive. For those days when the University of Texas is in session, e-scooter trips are shorter and durations are less, while effects on e-bicycles are not significant and the coefficient for docked bikeshare, while significant and negative is small. This implies that perhaps students tend to take shorter e-scooter trips; this is supported by anecdotal reports that they are widely used on campus between buildings.

Windier days reduce both distance and duration for e-scooters and e-bikes, with larger negative parameters in the e-bike models but no effect in the docked bikeshare model on duration. Rain also reduces the distance and duraton of e-scooters and e-bikes, with a larger effect on the latter. Paradoxically, rain actually increases docked bikeshare duration. Increases in average temperature increase duration and distance traveled of e-scooters and e-bicycles, but decrease the duration of use of docked bikeshare. Higher relative humidity reduces e-scooter duration and distance, has no statistically significant effect on e-bicycles (though coefficients are negative), and is actually associated with longer duration of docked bikeshare usage. A similar effect is found for excessive temperatures above 80 °F (26.7 °C). Overall, there is a larger impact from weather on e-bicycle usage than on e-scooter usage for both distance and duration of trips, especially from rain and wind.

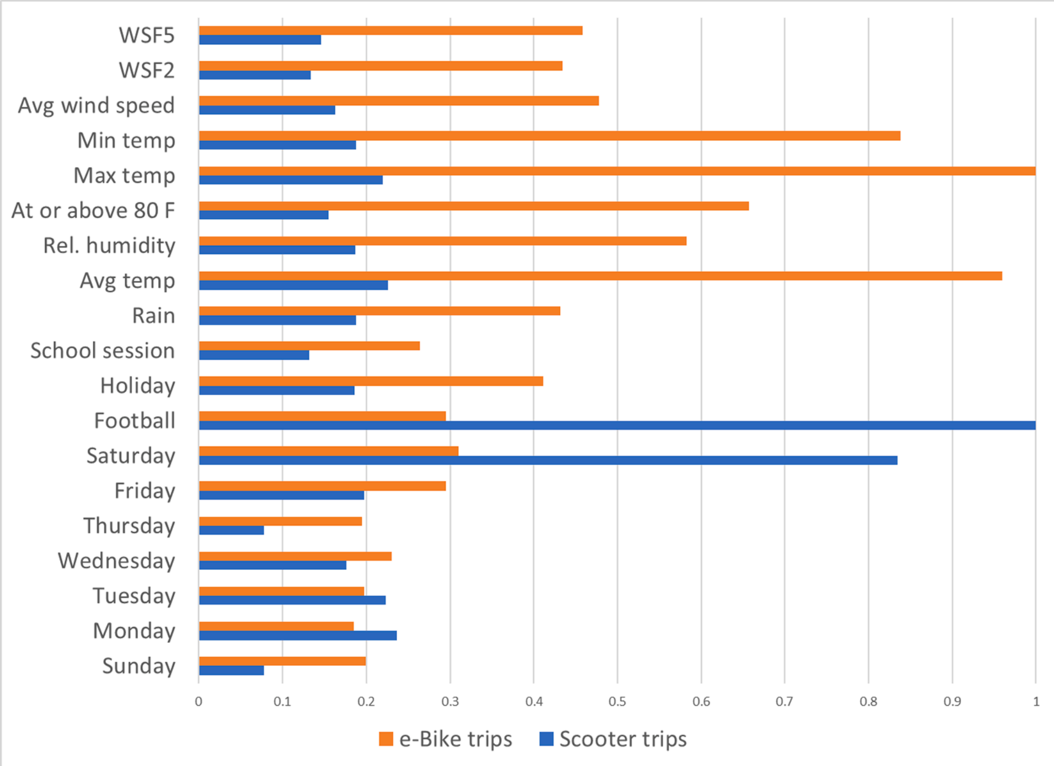

Fig. 5. Relative importance of parameters from Random Forest model, e-scooters and e-bike trips, without SXSW days in the model. Note: RMSE for e-scooter trip model: 1355.96; RMSE for bicycle trip model: 137.27. Importance levels are normalized to 1 for the variable that has the largest predictive effect. N = 355 for scooter trips and N = 352 for daily e-bike trips.

Table 9
Prais-Winsten regressions of distance and duration for e-scooters and bicycles.

	dep var. = e-scooter distance		dep var. = e-scooter duration		dep var. = e-bicycle distance		dep var. = e-bicycle duration		dep var. = bikeshare duration	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Holiday	**241.27**	**6.59**	**129.51**	**6.83**	**380.37**	**4.00**	**184.42**	**3.41**	10.19	0.88
Tuesday	**−41.36**	**−2.22**	**−29.56**	**−3.10**	**−114.14**	**−2.39**	**−61.53**	**−2.20**	3.03	0.47
Wednesday	**−61.44**	**−2.73**	**−42.22**	**−3.49**	**−141.80**	**−2.34**	**−69.69**	**−2.12**	8.91	1.27
Thursday	−27.87	−1.17	−13.57	−1.03	−66.03	−1.01	−8.49	−0.25	5.16	0.73
Friday	**54.21**	**2.27**	**55.45**	**4.21**	18.74	0.28	43.25	1.25	10.13	1.43
Saturday	**184.46**	**7.97**	**174.46**	**14.03**	**247.86**	**3.96**	**255.62**	**7.52**	**33.62**	**4.65**
Sunday	**212.74**	**11.30**	**178.25**	**18.46**	**352.01**	**7.20**	**261.89**	**9.21**	**19.97**	**3.07**
School in session	**−187.45**	**−7.96**	**−68.88**	**−3.64**	−67.90	−0.76	−18.78	−0.62	**−10.75**	**−2.13**
SXSW days	−9.19	−0.15	17.27	0.39	−297.22	−1.39	−35.02	−0.43	−5.75	−0.42
Football days	78.10	1.58	46.78	1.88	28.18	0.22	81.69	1.10	−15.68	−0.94
Average wind speed	**−8.40**	**−4.45**	**−4.89**	**−4.79**	**−19.69**	**−3.86**	**−12.78**	**−4.68**	0.58	1.04
Rain (inches)	**−49.90**	**−3.57**	**−19.41**	**−2.75**	**−100.20**	**−2.80**	**−65.15**	**−3.10**	8.95	1.90
Average daily temperature (°F)	**6.47**	**7.10**	**1.90**	**3.20**	**6.74**	**2.33**	**4.15**	**3.29**	**−0.52**	**−2.21**
Relative humidity (%)	**−2.70**	**−4.13**	**−1.08**	**−3.06**	−2.73	−1.55	−1.39	−1.47	**0.63**	**3.27**
At or above 80°F	**−90.48**	**−3.33**	**−56.68**	**−3.63**	−141.88	−1.77	**−104.78**	**−2.67**	**21.21**	**2.83**
Constant	**1405.95**	**18.37**	**644.37**	**13.08**	**2569.97**	**10.75**	**916.15**	**8.67**	22.11	1.11
Rho	0.48		0.72		0.69		0.39		0.17	
DW	1.27		1.05		0.74		1.26		1.66	
DW(final)	2.10		2.23		2.37		2.08		2.03	
N	365		365		362		362		365	
RMSE	115.21		64.72		320.38		166.96		35.53	
Adj-R^2	0.55		0.63		0.29		0.38		0.12	

5. Discussion and conclusions

There are several key take aways from this analysis. First, it is clearly important to control for special events in a city and how these affect usage of shared micromobility modes. A large technology-oriented event, such as SXSW, has a particular and probably idiosyncratic effect with large increases in usage. Days in which football games occur also have an impact on usage. In any case, this needs to be accounted for in any statistical model so that results are not distorted. There may be large events that occurred in Austin that I am unaware of that further affect results. The ability to offer these sort of services when special events occur provides a useful transportation mode for visitors, and this is apparent from the large peaks seen in the data.

Daily patterns of usage must also be controlled for. The larger usage of e-scooters on weekend days suggests these are potentially a popular recreational mode. While this result is only suggestive and based on the patterns of usage in the data it does suggest an avenue for further research into individual behavior. Other work has suggested e-scooters are used for recreation (Noland, 2019). The behavior of the student population is also ripe for further research into understanding how e-scooters are used. The results here suggest that the student population may be taking shorter e-scooter trips and again these are clearly serving a useful purpose for this population.

The main focus of this analysis is on the weather variables. Clearly weather has an impact on all three modes, but more so for e-bicycles. Lower temperatures, wind and rain reduce usage, distance, and duration of both modes, but in all cases impacts are greater for both bicycle modes. The surprising results for weather impacts on docked bikeshare duration might be due to the large reduction in usage over the time period of the data. The fact that duration of docked bikeshare trips has a postive association with rain suggests that the customer base contains only more dedicated cyclists, while other customers have shifted to the newer e-modes. These sort of cross-modal effects deserve more research.

Prior research has documented the impact of weather conditions on bicycle usage for utilitarian trips, as summarized in Heinen et al. (2010) in their review of studies of bicycle commuting. As these modes are exposed to the weather, this can make it difficult to convert people to use more sustainable modes of transportation. One of the primary amenities of a car (or any motorized mode) is protection from the elements. The use of e-scooters is also affected by weather, although my results suggest that bad weather has less of an impact on e-scooter usage than on e-bicycle and docked bikeshare usage (except for duration of trips). Nevertheless, there is still a negative effect of weather on e-scooter usage. For e-scooters this may be partially a reduction in recreational use. It seems likely that bad weather would deter many outside activities and future research could examine this in more detail.

Further research is needed to examine some of these effects in more detail and in cities with colder and wetter climates, compared to Austin. Any analysis of this type of data, whether for bikeshare or e-scooters does not provide evidence of user motivations as it is only based on examining the patterns of usage and in this case correlating with weather variables. Detailed survey work is needed to understand what type of trips these services are used for and how these are impacted by different weather conditions. Individual tolerance for discomfort obviously plays a role and additional research could investigate this in more detail. While policy makers can not directly affect the weather understanding what type of trips and who are most affected might provide guidance on providing alternatives.

Micromobility is offering the promise of a more sustainable transportation mode for short trips in cities. If weather is a deterrent this suggests that these modes will need to evolve to offer protection from the weather. However, this can make it difficult to maintain lightweight and more energy efficient mobility.

References

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32.

City of Austin, 2019. Shared Micromobility Vehicle Trips. Retrieved from https://doi.org/10.26000/030.000003.

Corcoran, J., Li, T., Rohde, D., Charles-Edwards, E., Mateo-Babiano, D., 2014. Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events. J. Transp. Geogr. 41, 292–305.

Gebhart, K., Noland, R.B., 2014. The impact of weather conditions on bikeshare trips in Washington, DC. *Transportation* 41 (6), 1205–1225.

Heinen, E., Van Wee, B., Maat, K., 2010. Commuting by bicycle: an overview of the literature. Transp. Rev. 30 (1), 59–96.

Kim, K., 2018. Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations. J. Transp. Geogr. 66, 309–320.

Mathew, J.K., Liu, M., Bullock, D.M., 2019. Impact of Weather on Shared Electric Scooter Utilization. Paper presented at the 2019 IEEE Intelligent Transportation Systems Conference (ITSC).

Nankervis, M., 1999. The effect of weather and climate on bicycle commuting. Transp. Res. Part A: Policy Pract. 33 (6), 417–431.

NOAA, 2019. National Centers for Environmental Information, Climate Data Online. Retrieved from https://www.ncdc.noaa.gov/cdo-web/.

Noland, R., 2019. Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. Transp. Find. https://doi.org/10.32866/7747 (April 29, 2019).

Sanders, R.L., Branion-Calles, M., Nelson, T.A., 2020. To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. Transp. Res. Part A: Policy Pract. 139, 217–227.

Saneinejad, S., Roorda, M.J., Kennedy, C., 2012. Modelling the impact of weather conditions on active transportation travel behaviour. Transp. Res. Part D: Transp. Environ. 17 (2), 129–137.

Schonlau, M., 2019. RFOREST: Stata module to implement Random Forest algorithm EconPapers. Retrieved from https://EconPapers.repec.org/RePEc:boc:bocode:s458614.

Sears, J., Flynn, B.S., Aultman-Hall, L., Dana, G.S., 2012. To bike or not to bike: seasonal factors for bicycle commuting. Transp. Res. Rec. 2314 (1), 105–111.

Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, DC. Transp. Res. Part A: Policy Pract. 134, 308–320.