Factors Influencing Electric Bike Share Ridership: Analysis of Park City, Utah

Article *in* Transportation Research Record Journal of the Transportation Research Board · April 2019

DOI: 10.1177/0361198119838981

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Abstract

In recent years, bike share programs have become more popular as they contribute to the move towards sustainable mobility in cities. Electric bike sharing, however, remains in the early stages of development. In contrast to traditional bikes, electric bicycles (e-bikes) provide an extra boost via an electric pedal-assist motor, thereby making it much easier to travel around a city with a hilly terrain, such as Park City, Utah. Based on an analysis of historical trip data of the Summit Bike Share system, in this paper, we present the system's performance experience and evaluate the factors affecting Park City's e-bike share ridership. We performed a Poisson regression analysis to investigate the influences of weather, temporal, and spatial variables on e-bike share usage. The regression results reveal that weather factors, including temperature and wind speed, significantly impact e-bike share usage. We also found that weekends, summer months, high population density, and proximity to public transit centers, recreational centers, and bike trails positively affect the demand for e-bikes. These findings can help the operators of Summit Bike Share to better understand the users of their e-bike share system, while also providing a guide for other e-bike projects currently in the planning stages.

Keywords: Electric bike share, weather factors, temporal factors, spatial factors, bike ridership, regression model

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1. Introduction

A bike share system (BSS), or public bike system, is a service that provides users with short-term access to public bicycles through an automatic check-out-and-return process. The concept of bike share originated in Amsterdam, Netherlands in the 1960s (Lin et al., 2013). It grew slowly in the early stages and then more rapidly in the 2000s with the development of information technology. This technology has made it very convenient for users to rent/return a bicycle, while providing operators with effective methods for bicycle tracking and management. As of 2014, there were bike share programs established in 712 cities around the world, with a total of 806,200 bicycles (Shaheen et al., 2014). Bike share programs bring a number of benefits to their users and to society, including access to an affordable and sustainable alternative to motorized public transport and private vehicles for short-distance trips; reduced fuel usage, emissions, noise, and congestion; improved health through physical exercise; and improved connectivity to other modes of transit (DeMaio, 2009; Mattson and Godavarthy, 2017; Kim, 2018).

Electric bicycles (e-bikes) have become increasingly popular in recent years, with the number of e-bikes having increased substantially in Europe, America, and especially China (Schleinitz et al., 2017). Compared with conventional human-powered bicycles, e-bikes reduce the required cycling effort and travel time, provide easier access to hilly terrain, better tolerance of high temperatures, and the potential to reach more distant locations. Despite these advantages, e-bikes have yet to be widely introduced in BSSs. Currently, the vast majority of BSSs use conventional bicycles, with only a handful of cities having adopted e-bikes. Possible reasons for this may include safety concerns, disruption to traffic, high cost, and operational complexity (Schleinitz et al., 2016; Campbell et al., 2016; Cherry et al., 2010).

Several BSSs in Europe are comprised fully or partially of e-bikes. Germany launched a BSS, Call A Bike, in Stuttgart in 2011 that offers both conventional bicycles and e-bikes. Call A Bike provides 60 e-bikes and 450 conventional bicycles at 44 stations (Olson et al., 2015). Milan, Italy, also has a combined BSS consisting of 3,800 conventional bicycles and 1,000 e-bikes distributed among 300 stations around the city (Fahrradportal, n.d.). The Bycyklen system in Copenhagen, Denmark, is an all-electric BSS that, by the fall of 2014, included 2,000 e-bikes and 3,000 docking points at 105 stations (Olson et al., 2015). In the U.S., the first e-bike share system (e-BSS) was a pilot tested with just two stations at the University of Tennessee-Knoxville

(UTK) in 2011, with system access designed for students, faculty, and staff of UTK (Langford et al., 2013). In 2015, the Zyp bike share system deployed 400 bikes in Birmingham, Alabama, of which 100 are e-bikes, making it the first large-scale public e-bike share program in the U.S. (Zyp BikeShare). Baltimore and San Francisco followed suit by integrating e-bikes into their existing BSSs. In July 2017, Summit County and Park City in Utah launched the first all-electric BSS in the U.S., called Summit Bike Share (Summit Bike Share). The Summit Bike Share system offers 88 e-bikes and nine stations to their users. Overall, while electric BSSs have yet to be widely implemented, with the rapid development of technology, it is likely that the next generation of bike share could be driven by e-bikes (Olson et al., 2015).

Although a number of studies regarding bike sharing have been published in recent years, there have been few analyses of electric BSSs. The main goal of this study is to evaluate data from the Summit Bike Share system, present the lessons learned from this e-bike share program, and use a regression model to investigate the possible factors that affect e-bike share usage. The results of this study can provide guidance to transportation agencies for planning and operating e-BSSs.

2. Related Studies

2.1 E-bike share

There are currently few studies about e-bike share. Cherry et al. (2010) discussed the possible challenges and operational requirements of developing an e-BSS. Langford et al. (2013) introduced the operational experiences of a pilot e-BSS at UTK. Later, Ji et al. (2014) developed a Monte Carlo simulation model for determining the required number of e-bikes and batteries for e-BSSs characterized by different demands and then demonstrated the model at the UTK e-bike share project. Thomas et al. (2015) proposed an implementation algorithm for the energy management design of e-BSSs. Campbell et al. (2016) conducted a mode choice survey in Beijing and developed a multinomial logit model to explore the factors that influence people's choice of a traditional bike or e-bike share. Ioakimidis et al. (2016) also analyzed users' attitudes towards e-BSSs and identified key factors that affect the usage of e-BSSs based on a survey conducted at the University of Mons. The authors of the above studies evaluated e-BSSs on the basis of data from either a small pilot project or survey. However, to better understand e-BSSs, analyzing data from a large-scale e-BSS could have more practical value. In this study, our objective is to fill this gap in the literature.

2.2 Factors affecting bike share ridership

In the literature, the weather has been considered to be a common factor affecting bike usage. Several researchers have focused on bicycling in general, with respect to the weather, including temperature, wind, and precipitation, and have found colder conditions to negatively impact cycling (Nankervis, 1999; Bergstrom and Magnusson, 2003; Flynn et al., 2012). Researchers have also discovered that recreational cyclists are more sensitive to weather conditions than commuter cyclists (Brandenburg et al., 2007), and weekend bike trips are more sensitive to weather conditions than weekday trips (Nosal and Miranda-Moreno, 2014). Recent studies have analyzed the effect of weather on BSSs. Gebhart and Noland (2014) studied Washington DC bike share data. By analyzing the hourly trip data of the Capital Bikeshare system, they found that bike share demand decreases in adverse weather conditions, such as very cold temperatures, rain, high humidity, and increased wind speed, but increases when temperatures reach the 90 °F range (32.2–37.2 °C). Faghih-Imani et al. (2014) examined the data of BIXI, the first major public BSS in Montreal, Canada, and the results showed increased usage of the BSS in good weather conditions. A study conducted by EI-Assi et al. (2017) concluded that temperatures are positively correlated with bike share ridership, and humidity level and snow are negatively correlated with bike share ridership. Mattson and Godavarthy (2017) found there to be a quadratic relationship between temperature and bike share usage. In their study, within the warm temperature range, bike share ridership increased as temperatures increased, but when temperatures reached a certain threshold value (81°F), ridership began to decrease, whereas at higher temperatures, the effect of temperature changes on ridership were reduced.

Researchers have also found bike share usage to vary temporally. Hampshire and Marla (2012) observed that the bike share usage patterns of BSSs in Barcelona and Seville are consistent with people's daily commuting behaviors. Faghih-Imani et al. (2014) found a reduction in bicycle usage on weekends. Seasonal and daily bike-share trip variations were investigated in the study conducted by EI-Assi et al. (2017). Faghih-Imani et al. (2017) also found a time-of-day variation in bike share usage in Barcelona and Seville, Spain. In a study of the ridership data of the Great Rides Bike Share system in Fargo, North Dakota, Mattson and Godavarthy (2017) observed a positive correlation between ridership and the hours of daylight, and also found ridership to be higher on weekdays for stations located on the North Dakota State University campus.

Another factor that has been widely considered in bike share usage studies is the spatial factor. Buck and Buehler (2012) analyzed the spatial determinants of bike share usage of the Capital Bikeshare system in Washington, DC. The results revealed that bike lane supply and population density near the bike stations positively affect bike demand. Daddio (2012) also performed a regression analysis on the ridership data of the Capital Bikeshare system and concluded that proximity to retail amenities, Metrorail stations, and the BSS center were positively correlated with bike share trip generation. Similar studies have been conducted by other researchers in the evaluation of spatial variables such as land use, built environment, and bicycle infrastructure and their effects on bike share ridership (e.g., Hampshire and Marla, 2012; Rixey, 2013; Nair et al., 2013; Fishman et al., 2014; Wang et al., 2015). Based on these studies, higher ridership levels have generally been found to be correlated with proximity to educational centers, commercial centers, and public transit stations; more bicycle facilities; and higher population and employment densities.

In this study, we examined the influence of weather, temporal, and spatial variables at the station level on the e-bike share usage of the Summit Bike Share system.

3. Summit Bike Share System

Summit Bike Share, launched on July 19, 2017, is the first bike share program in the U.S. with a fleet consisting entirely of e-bikes. At the time of launch, the program distributed 88 pedal-assist e-bikes among nine stations at Park City's Kimball Junction, Canyons, and Old Town Transit Center (as shown in Figure 1), to enable both local residents and tourists to more easily explore the area.

The e-bikes and docking stations, as shown in Figure 2, are provided by Bewegen. The e-bikes have a low center of gravity and high-capacity brakes that ensure a comfortable and safe riding experience for users. The propulsion motor on the bikes helps provide an extra boost when pedaling, making it much easier to commute in a city with mountainous terrain, like Park City. When users start pedaling, the motor starts and will assist the bike up to 14.5 mph to meet with the speed limit of 15 mph for the e-bikes on the multi-use pathways in Park City (E-Bikes Safety & Use). When users stop pedaling or reach 14.5 mph, the motor turns off. When the bike is checked back into the docking station, it re-charges automatically. Typically, a fully charged e-bike can provide a full day of service and still have battery life left over. The price of a single trip is \$2 for the first 45 minutes, and then \$2 for each additional 30 minutes. There are also several discounted plans for regular users: \$18 weekly, \$30 monthly, and \$90 yearly. In 2017, from July 20th through November, the e-BSS was available to the public 24/7. During the rest of the year, the bikes are taken into storage because of the cold climate conditions.

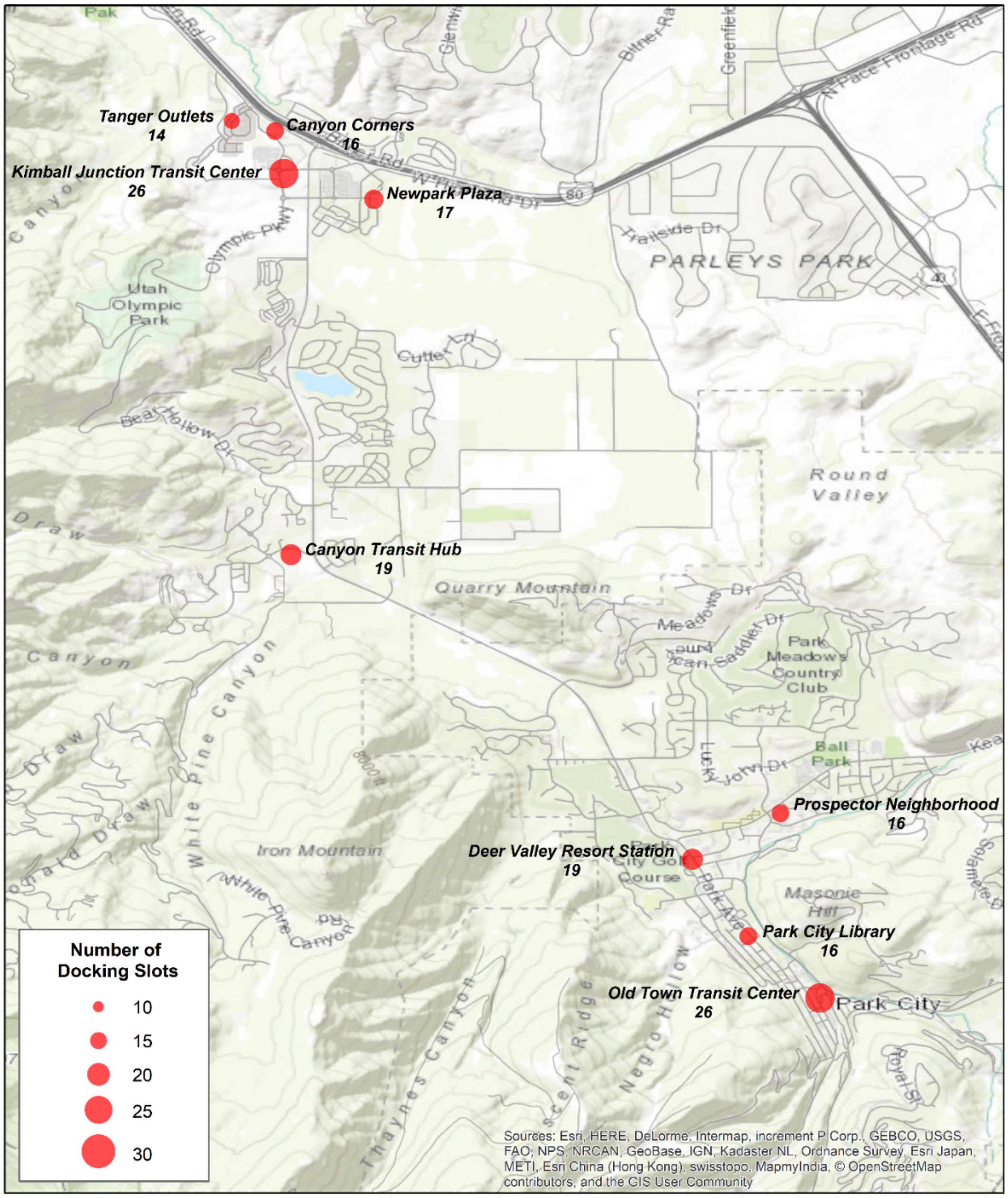

Figure 1. Summit Bike Share station location map.

Figure 2. Summit Bike Share.

4. System Performance

We obtained e-bike usage statistics from the Summit Bike Share program for its first opening period (July 20 to November 3, 2017). The dataset contains the start time, end time, start station, end station, bicycle number, user membership type, and user age for each trip. In addition, the GPS device mounted on the bike records the coordinates of the bike whenever the bike is in use, therefore the dataset also contains GPS data for each trip. We processed and analyzed these raw data for this study.

A total of 7,921 trips were generated during the opening period, including both inter-station and intra-station trips. This statistic excludes trips with a duration of one minute or less, because these trips may not be typical of the usage of the BSS. This short trip rule has also been applied in other studies (e.g., Zhou, 2015; Mattson and Godavarthy, 2017). The majority of these trips (84.51%) were taken by non-regular users who bought a single-trip pass, with only a small portion (15.49%) being taken by users with a weekly, monthly, or yearly pass, whom we refer to as regular users (as shown in Figure 3). This is a reasonable finding, because the Summit Bike Share system is new to the city and it may take time for residents to accept it for daily use. It is also possible that most users are tourists rather than local residents because of Park City's reputation as a tourist hotspot in Utah. As such, we found most trips have been generated by one-time users.

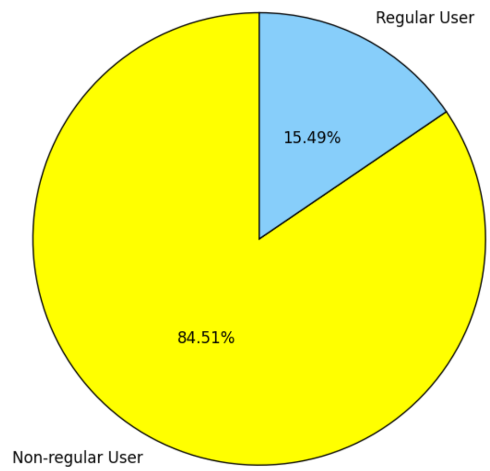

Figure 3. User membership distribution.

We obtained the user age distribution for Summit Bike Share and compared it with the resident age distribution of Summit County (Source: Bigelow et al., 2011). As we can see in Figure 4, there are two peaks for Summit Bike Share users: ages 20 to 30 and 45 to 55, and one peak for Summit County residents: age 45 to 55. The proportion of residents aged 45 to 55 is nearly equal to the proportion of bike share users aged 45 to 55, whereas the proportion of residents aged 20 to 30 is obviously less than the proportion of bike share users within that range, which may indicate that young people are more willing to try the new e-BSS.

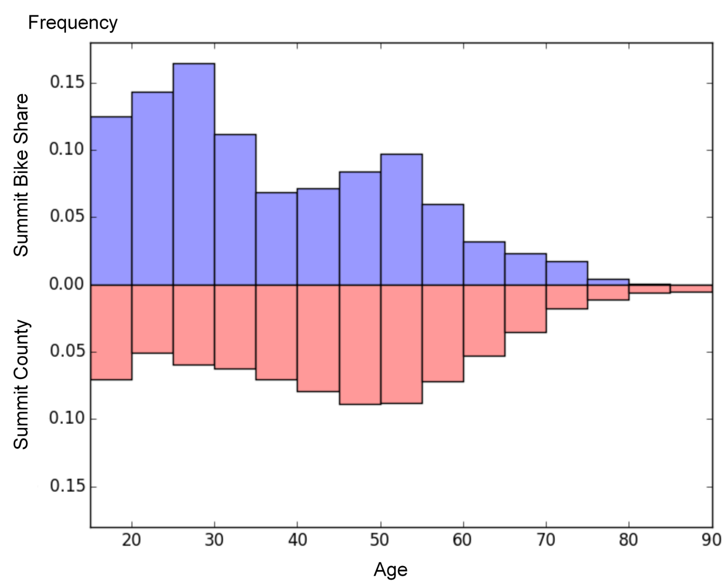

Figure 4. Summit Bike Share user age distribution versus Summit County resident age distribution.

We calculated the trip distance for each trip based on the GPS data. Figure 5 shows the trip distance distribution of the generated trips, and we can observe that the majority of trips are within 10 miles, with a small portion of trips having a distance of more than 10 miles. The average trip distance is 4.75 miles. According to the study of Zhang and Yu (Zhang and Yu, 2016), the average trip distance of the Chicago Divvy BSS, which is a conventional BSS, is around 1.24 miles (≈ 2 km). The average trip length of the conventional BSSs in Boston (Hubway) and in Washington D.C. (Capital Bikeshare) have been found to be just over a mile (Alta Planning + Design, 2012). Apparently, people tend to travel farther by electric bikes than they do by normal bikes, which demonstrates the advantages of e-bikes: speed and reduced rider effort.

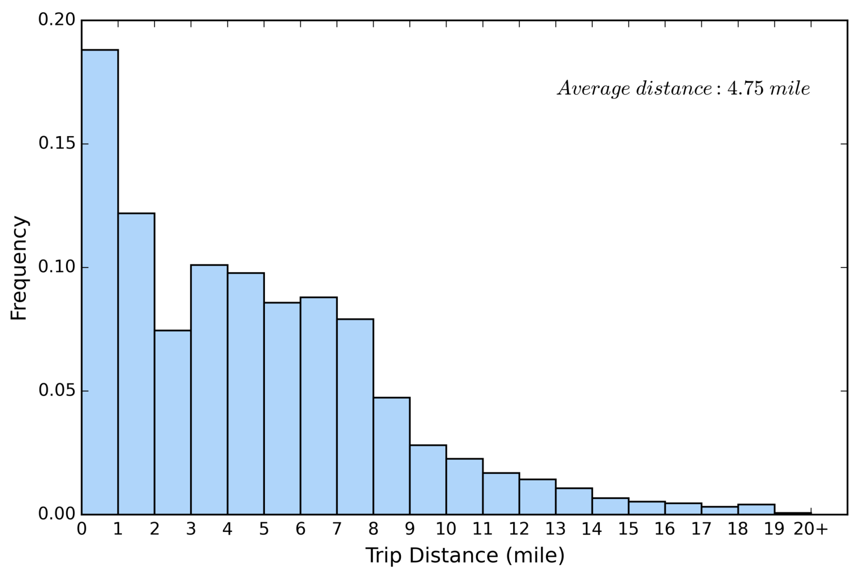

Figure 5. Trip distance distribution.

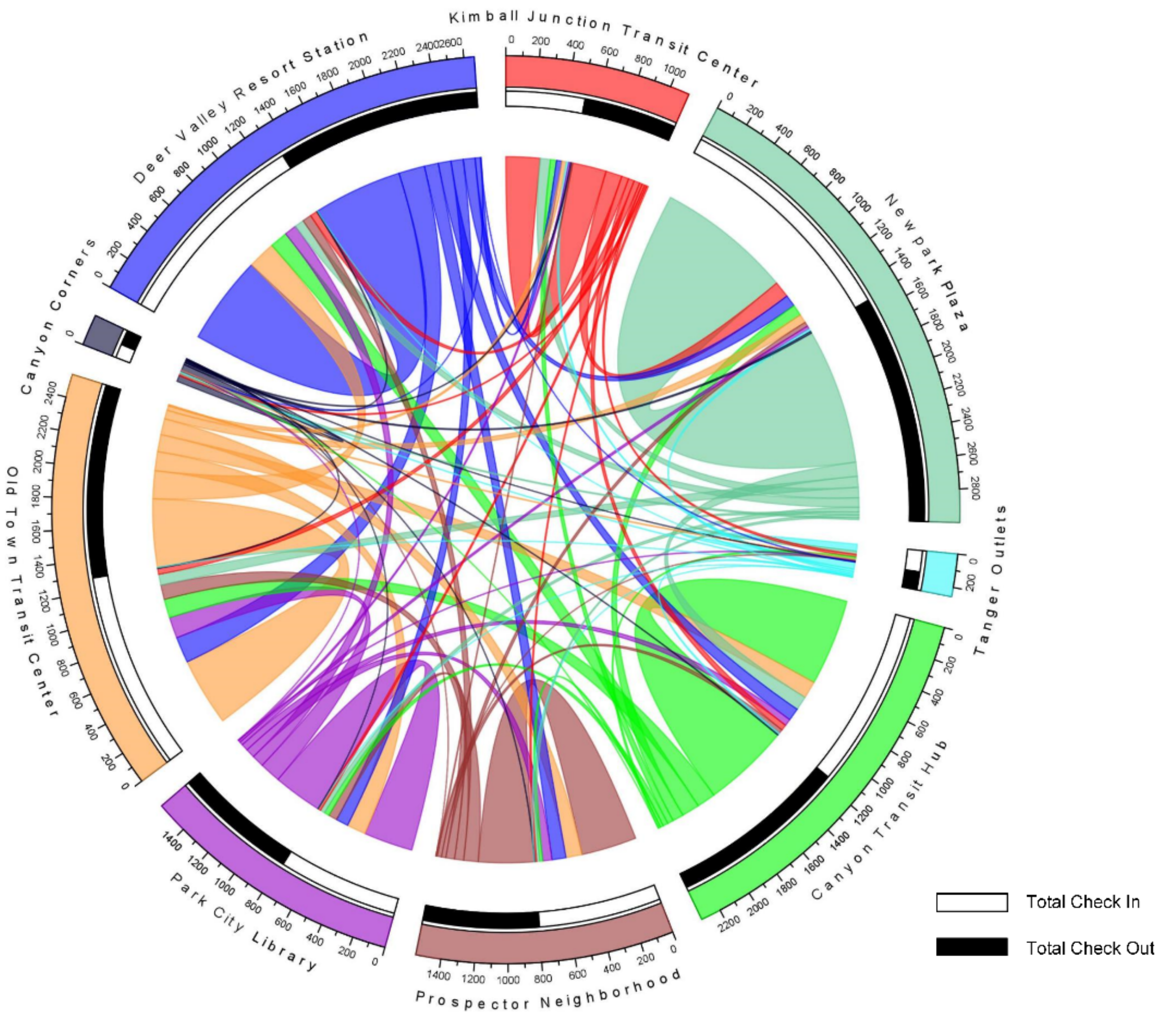

Figure 6. Trip distribution among stations.

Figure 6 shows the number of trips between each station pair. The outer track represents the total number of trips generated at each station, the black portion of the inner track indicates the trips that start from the station, and the white portion of the inner track indicates the trips that end at the station. For example, for the Deer Valley Resort station, there were approximately 1,300 check-ins to the station and approximately 1,400 check-outs from the station. From Figure 6, we can observe that unlike a conventional BSS, for which most trips have different check-in and check-out stations (e.g., Zhou, 2015; Mattson and Godavarthy, 2017), many trips generated in this all-electric BSS are intra-station trips. One possible reason could be that many tourists checked out e-bikes to sightsee the Park City area and then returned the bikes to the same bike station near where they had parked their cars, since most users were non-regular users, as shown in Figure 3. We can also observe in Figure 6 that the Newpark Plaza, Deer Valley Resort, and Old Town Transit Center stations are the three favorite stations, and the Tanger Outlets and Canyon Corners stations are the least favorite.

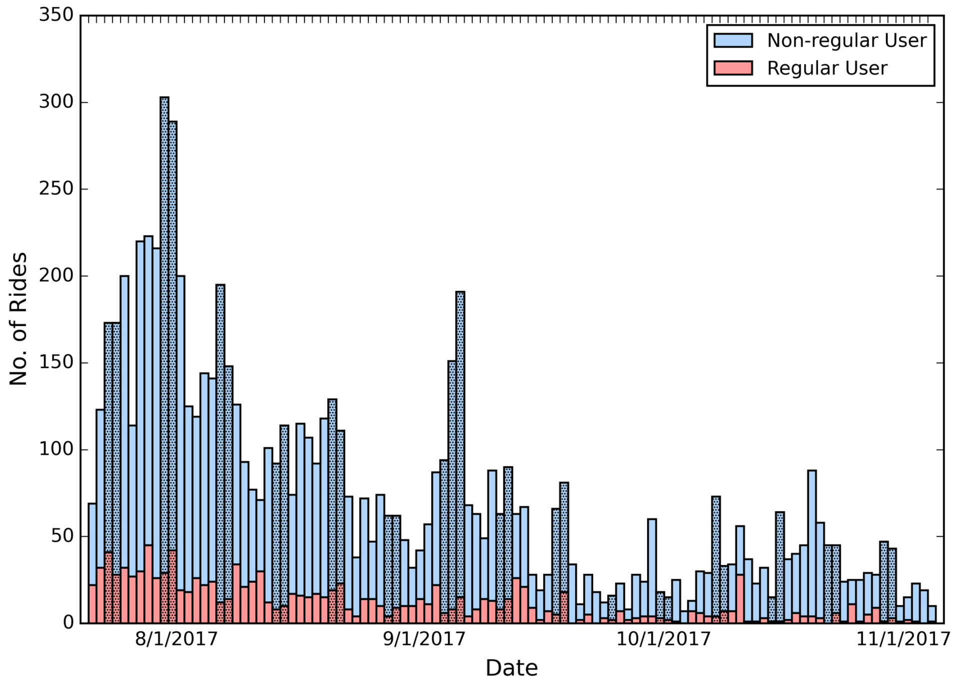

Figure 7. Daily trip over time.

We plotted the daily trip distribution in Figure 7, in which trips generated by regular and non-regular users are distinguished by color, and weekends or holidays are highlighted by darker shades. In the figure, we can observe that over time, there is a downward trend in the number of trips generated by both types of users. Additionally, there were relatively more trips taken in July and August and fewer in September, October, and early November. This may be due to the changes in climate conditions in different months or due to the fact that there are usually more tourists in summer. In the next section, we further analyze the possible reasons for these findings. We can also observe that in terms of non-regular users, generally more trips were taken on weekends and holidays than on weekdays, which is consistent with our previous idea that most users were tourists, as a result, recreational trips increased on weekends. For regular users, there is no such obvious trend.

6. Regression Modeling

To analyze the effects of weather, temporal, and spatial factors on e-bike ridership in the Summit Bike Share system, we developed a Poisson regression model, which is one of the most widely used models for multivariate count data modeling. The general formulation of Poisson regression is as follows:

$$\log\big(E(\boldsymbol{Y})\big) = \boldsymbol{\alpha} + \boldsymbol{\beta}'\boldsymbol{X}$$

where $\boldsymbol{Y}$ is a vector of the dependent variables, $\boldsymbol{\alpha}$ is the intercept item, $\boldsymbol{\beta}$ is a vector of the regression coefficients, and $\boldsymbol{X}$ is a vector of the independent variables.

In this study, the dependent variable is the number of rides per day per station. Below, we describe the independent variables used to determine ridership:

As weather factors, we included four weather elements in the dataset: 1) daily average temperature (°F), 2) daily visibility (miles), 3) daily average wind speed (knots), and 4) daily precipitation (inches). We extracted the daily weather data for Park City, UT from historical weather data in the weather information website Weather Underground (Weather Underground, 2018). We expected ridership to decrease with decreases in temperature and visibility and increases in wind speed and precipitation.

Based on the analysis results described in section 5, we know that temporal factors could greatly impact ridership. To explore this idea, we introduced two dummy variables, 'DayType' and "Summer" into our model, where 'Daytype' indicates whether a day is a weekday or on a weekend (including national holidays), and 'Summer' indicates whether or not a day occurs in the summer months. Our expectation was that the ridership of the e-BSS would be higher on weekends and summer days.

Important spatial factors that could influence e-bike ridership of the Summit Bike Share system include the bike station capacity, the proximity of the station to a transit center, proximity of the station to a recreational center (including shopping and recreation areas), proximity of the station to a bike trail, and the density of the residential population near the station. We obtained population data from the 2010 Census block data (U.S. Census Bureau, 2010), and calculated the population near a transit station by totaling the population in the census blocks that are within 0.25 miles of the station.

The Poisson regression model we used in this study is formulated as follows:

$$\log(NoRides_{it}) = \beta_0 + \beta_1 AveTemp_t + \beta_2 Visibility_t + \beta_3 WindSpeed_t + \beta_4 PrecipAmount_t$$
$$+\beta_5 DayType_t + \beta_6 Summer_t + \beta_7 Capacity_i + \beta_8 TransitCenter_i + \beta_9 RecrCenter_i$$
$$+\beta_{10} BikeTrail_i + \beta_{11} Population_i,$$

where $NoRides_{it}$ = number of rides at station i in day t, $AveTemp_t$ = average temperature on day t, $Visibility_t$ = visibility on day t, $WindSpeed_t$ = average wind speed on day t, $PrecipAmount_t$ = total precipitation amount on day t, $DayType_t$ = dummy variable for weekdays (1 for weekdays and 0 otherwise), $Summer_t$ = dummy variable for summer time (1 for summer time and 0 otherwise), $Capacity_i$ = number of docking slots at station i, $TransitCenter_i$ = dummy variable for station near transit center (1 means station i is near a transit center and 0 otherwise), $RecrCenter_i$ = dummy variable for station near recreational center (1 means station i is near a recreational center and 0 otherwise), $BikeTrail_i$ = dummy variable for station near a bike trail (1 means station i is near a bike trail and 0 otherwise), $Population_i$ = population near station i, and β_0 = intercept, β_1-β_{11} = coefficients of the independent variables.

7. Results and Discussion

To estimate the impact of weather, temporal, and spatial variables on e-bike ridership, and to evaluate the differences between the behaviors of regular and non-regular users, we considered three groups of dependent variables: 1) total number of rides generated by both regular and non-regular users, 2) number of rides generated by regular users, and 3) number of rides generated by non-regular users. Then, we applied the proposed model to each of these variables. We obtained our results using the PROC GENMOD procedure in the SAS software suite. Tables 1 to 3 show summaries of the obtained results.

Two statistical measures are generally used to assess the goodness of fit of a Poisson regression model: the scaled deviance and Pearson Chi-square statistical measures. If a model is adequate, the expected value of both measures should be equal or close to their degrees of freedom (DF) (Pedan, 2001). In the regression results shown in Tables 1 to 3, we can see that for all the three models, the values of both the scaled deviance/DF and Pearson Chi-square/DF are close to 1, indicating that the models fit well.

The estimated coefficients indicate the change in the logs of the expected ridership for a one-unit increase in an independent variable, when the other variables are held constant.

In Tables 1 to 3, we can observe that the weather variables 'Visibility' and 'PrecipAmount' are not significant in the three models, i.e., there is no statistically significant evidence of any log-linear relationship between e-bike ridership and 'Visibility'/'PrecipAmount', which means that, based on our data, visibility and daily precipitation amount did not significantly impact e-bike ridership.

'Capacity,' i.e., the number of docking slots at each station, is also not significantly related to e-bike ridership in the three models. However, in other studies (e.g., El-Assi et al., 2017; Mattson and Godavarthy, 2017), the capacity of the bike stations has been found to generally have a significantly positive correlation with bike share ridership. The non-significant result here may indicate that the configuration of the docking slots for the e-bike stations could be improved, i.e., e-bike share activity may increase if the operators adjust the layout of the docking slots.

All the other variables, except 'DayType' in Table 2 and 'WindSpeed' in Table 3, are significant. The non-significant variable 'DayType' for regular users indicates that regular users are not as sensitive to weekdays as non-regular users. This result is consistent with our observations in Figure 7. The non-significant variable 'WindSpeed' for non-regular users indicates that non-regular users are not as sensitive to daily wind speed as regular users.

The signs of the coefficients for daily average temperature and daily average wind speed are positive and negative, respectively, which indicates that higher temperature and lower wind speed contribute to an increase in ridership, as expected.

The variable 'DayType' in Tables 1 and 3 is significant with the expected negative coefficient. These results confirm that non-regular users are more likely to travel on weekends and holidays. 'Summer' has a positive coefficient in all three models, which means there is more e-bike ridership in summer than in other months.

The spatial variables 'TransitCenter,' 'RecrCenter,' 'BikeTrail,' and 'Population' have positive coefficients, indicating that proximity to a transit center, recreational center, and bike trail, and the density of the residential population all positively influence e-bike ridership.

Table 1

Model results for total number of rides

Variable	Parameter Estimate	Standard Error	P > Chi-Square
$Intercept$	-1.0340	0.8474	0.2224
$AveTemp_t$	0.0308	0.0038	<.0001**
$Visibility_t$	0.0239	0.0753	0.7511
$WindSpeed_t$	-0.0868	0.0379	0.0218*
$PrecipAmount_t$	-0.0642	0.1175	0.5850
$DayType_t$	-0.4136	0.0554	<.0001**
$Summer_t$	0.5005	0.0856	<.0001**
$Capacity_i$	-0.0107	0.0121	0.3801
$TransitCenter_i$	1.6455	0.1637	<.0001**
$RecrCenter_i$	1.1484	0.1161	<.0001**
$BikeTrail_i$	0.3951	0.0861	<.0001**
$Population_i$	0.0029	0.0002	<.0001**

Scaled Deviance/DF: 1.0000

Scaled Pearson Chi-Square/DF: 1.1300

Note: * indicates significance at 0.05 level; **indicates significance at 0.01 level

Table 2

Model results for number of rides generated by regular users

Variable	Parameter Estimate	Standard Error	P > Chi-Square
$Intercept$	-3.1925	1.2260	0.0092**
$AveTemp_t$	0.0311	0.0059	<.0001**
$Visibility_t$	0.0593	0.1078	0.5821
$WindSpeed_t$	-0.2171	0.0574	0.0002**
$PrecipAmount_t$	-0.1051	0.1686	0.5331
$DayType_t$	0.0129	0.0856	0.8806
$Summer_t$	0.6859	0.1298	<.0001**
$Capacity_i$	-0.0238	0.0167	0.1537
$TransitCenter_i$	1.7975	0.2258	<.0001**
$RecrCenter_i$	0.9315	0.1706	<.0001**
$BikeTrail_i$	0.5538	0.1313	<.0001**
$Population_i$	0.0029	0.0003	<.0001**

Scaled Deviance/DF: 1.0000

Scaled Pearson Chi-Square/DF: 1.2821

Note: * indicates significance at 0.05 level; **indicates significance at 0.01 level

Table 3

Model results for number of rides generated by non-regular users

Variable	Parameter Estimate	Standard Error	P > Chi-Square
$Intercept$	-1.1577	0.8994	0.1980
$AveTemp_t$	0.0309	0.0040	<.0001**

$Visibility_t$	0.0170	0.0801	0.8350
$WindSpeed_t$	-0.0638	0.0398	0.1085
$PrecipAmount_t$	-0.0556	0.1249	0.6563
$DayType_t$	-0.4865	0.0584	<.0001**
$Summer_t$	0.4672	0.0901	<.0001**
$Capacity_i$	-0.0081	0.0130	0.5356
$TransitCenter_i$	1.6143	0.1751	<.0001**
$RecrCenter_i$	1.1826	0.1229	<.0001**
$BikeTrail_i$	0.3697	0.0905	<.0001**
$Population_i$	0.0029	0.0002	<.0001**

Scaled Deviance/DF: 1.0000
Scaled Pearson Chi-Square/DF: 1.1522
Note: * indicates significance at 0.05 level; **indicates significance at 0.01 level

8. Conclusion

Despite the increasing popularity of bike share systems around the world, electric bikes have not yet been widely introduced to bike share fleets, and only a few studies have focused on e-bike share systems. In this study, we analyzed the Summit Bike Share system in Park City, Utah—the first all-electric bike share system in the U.S.—and identified the user characteristics and usage patterns of this new system. We found that 85% of the e-bike trips were made by non-regular users, only 15% were made by regular users, young people tend to use the e-bike share system more often, people tend to use e-bikes for longer trips, more trips are generated on weekends than on weekdays, and more trips are made in summer months. To better understand the factors affecting the ridership of this system, we developed a Poisson regression model to estimate the impacts of weather, temporal, and spatial variables on e-bike share usage. We applied this ridership model, which is based on trips per day per station, to three scenarios to determine the trips generated by different groups. The results show that higher daily temperature and lower wind speed are positively and significantly related to higher rates of e-bike ridership. In addition, bike volumes tended to be higher at stations near a public transit center, a recreational center, or a bike trail, and in areas with a higher population density. The results also identified some differences between this e-bike system and some regular bike share systems: the usage of this e-bike share system was higher on weekends whereas a reduction in bicycle usage on weekends has been found in regular BSSs (e.g., Miranda-Moreno and Nosal, 2011; Faghih-Imani et al., 2014; Mattson and Godavarthy, 2017). This finding may indicate that Park City attracts more casual users to its e-bike share system than regular users who commute to their workplaces. The results and findings of this study provide useful information for the planning and operation of future.

Acknowledgment

The study was partially sponsored by the U.S. Department of Energy (DE-EE0007997). The views expressed are those of the authors and do not reflect the official policy or position of the project's sponsors.

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