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

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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. The Summit Bike Share system in Park City is the nation's first fully electric bike share system (e-BSS). Based on an analysis of historical trip data of Summit Bike Share, in this paper, we presented the system's performance experience and evaluated the user characteristics and travel behavior. We further performed a Poisson regression analysis to investigate the factors that influence the e-bike share usage of this e-BSS. 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, proximity to public transit centers, recreational centers, and bike trails positively affect the demand for e-bikes. The findings of this paper can help the operators of Summit Bike Share to better understand their users and their e-BSS, while also providing a guide for other e-bike projects currently in the planning stages.

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 (*1*). 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 (*2*). 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 (*3-5*). That being said, conventional bikes for bike share programs have their limitations. For example, it is extremely laborious for people to use conventional bikes in cities with hilly terrain. In addition, bikes may accumulate in low-lying areas of hilly cities, requiring substantial efforts to rebalance the bike share system.

Electric bicycles (e-bikes) could be a potential solution to these above mentioned issues. E-bikes have become increasingly popular in recent years, with the number of e-bikes having increased substantially in Europe, America, and especially China (*6*). 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 not been widely introduced in BSSs. Currently, the vast majority of BSSs use conventional bicycles, with only a handful of cities having adopted e-bikes. Possible barriers to introducing e-bikes into bike share systems may include several aspects. First, e-bikes are much more expensive than conventional bikes. Second, it is more complicated to operate an e-bike share system (e-BSS) because e-bikes require proper power supply. Both parking and rebalancing strategies must take into account the charging needs of e-bikes. Third, regulatory issues could restrict e-bike usage. About half of U.S. states classify e-bikes as motor vehicles and require licensing, registration, and even insurance for riding e-bikes; some cities and areas do not allow e-bikes on trails and sidewalks (*7*).

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 (*8*). Milan, Italy, also has a combined BSS consisting of 3,600 conventional bicycles and 1,000 e-bikes distributed among 300 stations around the city (*9*). 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 (*8*). In the U.S., the first 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 (*10*). 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 bike share program that partially adopt e-bikes in the U.S. (*11*). 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 (*12*). The Summit Bike Share system offers 88 e-bikes and nine stations to their users. Overall, while e-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 (*8*).

Although a number of studies regarding bike sharing have been published in recent years, there have been few analyses of e-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 future planning of e-BSSs.

RELATED STUDIES

E-bike Share

There are currently few studies about e-bike share. Cherry et al. (*13*) discussed the possible challenges and operational requirements of developing an e-BSS. Langford et al. (*10*) introduced the operational experiences of a pilot e-BSS at UTK. Later, Ji et al. (*14*) 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. (*15*) proposed an implementation algorithm for the energy management design of e-BSSs. Campbell et al. (*16*) 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. (*17*) 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 values, for example, it can provide operational practices that can be used as a reference for future e-BSSs; operators could introduce incentive policies to the system to increase e-bike share use. In this study, our objective is to fill this gap in the literature.

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 (*18-20*). Researchers have also discovered that recreational cyclists are more sensitive to weather conditions than commuter cyclists (*21*), and weekend bike trips are more sensitive to weather conditions than weekday trips (*22*). Recent studies have analyzed the effect of weather on BSSs. Gebhart and Noland (*23*) 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. Faghih-Imani et al. (*24*) 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. (*25*) 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 (*4*) 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, whereas at higher temperatures, the effect of temperature changes on ridership were reduced, and when temperatures reached a certain threshold value (81°F), ridership began to decrease.

Researchers have also found bike share usage to vary temporally. Hampshire and Marla (*26*) 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. (*24*) 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. (*25*). Faghih-Imani et al. (*27*) 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 (*4*) 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 (*28*) 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 (*29*) 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., *26*; *30-33*). 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.

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 (Source: *34*), 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 (*35*). 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 2017, the bikes were taken into storage because of the cold climate conditions.

"place FIGURE 1 about here"

"place FIGURE 2 about here"

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, 107 days). 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 trips (trip with different origin and destination station) and loop trips (trip with the same origin and destination station). 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., *4*; *36*).

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. Since Park City has the reputation of being a tourist hotspot in Utah, and there was a considerable number of one-time users in this e-BSS, we assume that most of the e-bike users were tourists. Tourists may have different characteristics than local users, and these two groups may have totally different trip purposes (e.g., sightseeing, shopping, and recreation versus point-to-point transportation). In this study, we investigated the characteristic and travel behavior of the regular users and non-regular users separately to better understand the e-bike usage pattern of the Summit Bike Share system.

First, we obtained user age distributions of both regular and non-regular users and respectively compared them with the resident age distribution of Summit County (Source: *37*), as shown in Figure 3. We can observe that the age distribution of Summit County resident is near normal distribution and the middle-aged residents (age 45 to 55) have the largest two bins in the histogram. For regular users in the Summit Bike Share system, people aged 50 to 55 has the largest proportion, followed by people aged 25 to 30. As for non-regular users, younger people (age 15 to 35) accounts for the largest proportion. The results indicate that e-bike share attracts both young people and middle-aged people, and it is especially favored by middle-aged people for regular use probably because of its time-saving and labor-saving features. We note that previous literature Wang et al. (*38*) also analyzed the bike share trip productions by different age groups and their observations are different from our results. In their study, the usage data of New York's Citi Bike, a conventional bike share system, were analyzed. The authors found that people aged between 28 and 37 years old made the largest number of bike share trips. Other studies also revealed that conventional bike share is more attractive to younger adults (e.g., *39-42*). The differences between the findings of conventional bike share systems and this study may imply that e-bike share has its unique advantages and can attract different groups of users.

"place FIGURE 3 about here"

Second, we obtained trip distribution for both user types, as shown in Table 1. We visualized this origin-destination table as circular plots (as shown in Figure 4) to clearly show the trip patterns among the e-bike stations. In Figure 4, 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. The thickness of the curved links corresponds to the number of trips. For example, in Figure 4 (a), for the Newpark Plaza station, there were approximately 470 check-ins to the station and approximately 510 check-outs from the station. We expected to observe more commuting-based inter-station trips of regular users. However, from Figure 4, we found that for both user types, a large portion of the generated trips were loop trips. Therefore, it is reasonable to infer that most users in this e-BSS, even regular users, utilized e-bikes for recreational purposes (e.g., sightsee the Park City area) instead of commuting purposes. We can also observe in Figure 4 that the Newpark Plaza station is a very popular station for both regular and non-regular users, and the Tanger Outlets and Canyon Corners stations are the least favorite stations. However, according to Figure 1, Tanger Outlets, Canyon Corners, and Newpark Plaza have similar number of docking slots. System operators of the Summit Bike Share system may consider to adjust the number of docking slots for these stations to make the best use of the infrastructure.

“place TABLE 1 about here”

“place FIGURE 4 about here”

Third, trip distance for each trip was calculated based on the GPS data and Figure 5 shows the trip distance distribution for regular and non-regular users. For both groups, 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 of regular users is 4.90 miles, and the average trip distance of non-regular users is 4.65 miles, and the difference between regular and non-regular users is statistically significant at 0.05 level. According to the study of Zhang and Yu (*43*), 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 (*44*). Apparently, people tend to travel farther by electric bikes than they do by normal bikes, which demonstrates the advantages of e-bikes: reduced rider effort.

“place FIGURE 5 about here”

Furthermore, we plotted the daily trip distribution in Figure 6, 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 assumption that most non-regular users were tourists, as a result, recreational trips increased on weekends. For regular users, there is no such obvious trend.

“place FIGURE 6 about here”

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 (*45*). 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 previous section, 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 (*46*), 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:

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

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, $PrecipAmo_t$ = 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, $TransitCen_i$ = dummy variable for station near transit center (1 means station i is near a transit center and 0 otherwise), $RecrCen_i$ = 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.

REGRESSION RESULTS

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. Table 2 shows the summaries of the obtained results.

"place TABLE 2 about here"

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) (*47*). In the regression results shown in Table 2, we can see that for all three models, the values of both 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 Table 2, we can observe that the weather variables 'Visibility' and 'PrecipAmo' 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'/'PrecipAmo', 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., *4*; *24*), 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 number of the docking slots in the e-bike stations was not quite consistent with the e-bike share activity and the system reliability may be improved if the operators properly adjust the docking slots.

All the other variables, except 'DayType' for regular users and 'WindSpeed' for non-regular users, are significant. The non-significant variable 'DayType' for regular users indicates that for regular users, there is no significant difference between weekdays and weekends in terms of e-bike travel volume. This result is consistent with our observations in Figure 6. 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' for total number of rides and for non-regular users 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 'TransitCen,' 'RecrCen,' '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.

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.

Park City is a popular tourist city with plenty of hills. The introduction of the Summit Bike Share system to Park City aims at providing a convenient way for both residents and visitors to get around the city as well as cutting down traffic congestion and air pollution. It turns out that the initial public response to this e-BSS was good: there were nearly 8,000 effective e-bike trips for a combined 38,000 miles in the first opening period. A large amount of gasoline fuel was saved and emissions were avoided by the use of the e-bikes.

Through analyzing the e-bike share data, we found that 85% of the trips were made by non-regular users, only 15% were made by regular users. It is most likely that the majority of the users were tourists. We analyzed the age distribution, trip distribution, trip distance distribution, and daily trip of the e-BSS by differentiating between regular and non-regular users. The statistics imply that the e-BSS was most liked by young and middle-aged people and most people rent and returned e-bikes to the same bike station, which means most of the users utilized the e-bike share in Park City for other purposes (e.g., recreation purpose) rather than commuting to work. Maybe in the future, when the system becomes larger and more reliable (e.g., through properly adjusting station capacity), the number of regular trips will increase. The trip distance distribution shows that even in a hilly terrain area, this e-BSS has a average travel distance of about 5 miles, which is much longer than the average distance of a conventional bike share system like Chicago Divvy BSS (*37*), and Capital Bikeshare (*38*). This finding indicates that the e-bike share users were willing, and more importantly, able to travel long distances. Cities, espectially tourism cities or hilly cities, who plan to launch a bike share system in the future may consider adopting e-bikes.

In addition to the trip data analysis, we developed a Poisson regression model to better understand the factors affecting the ridership of this e-BSS. We applied the proposed ridership model, which is based on trips per day per station, to three scenarios to evaluate 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. We also found that more trips were generated on weekends than on weekdays, and more trips were made in summer months, which further supports our hypothesis that most users of the e-BSS were vistors rather than local residents. The differences between the regression results of regular user model and non-regular user model show that non-regular users were not as sensitive to daily wind speed as regular users, and non-regular users were more likely to travel on weekends and holidays. From both the data analysis results and the regression results, we found that the number of docking slots is not significantly related to the e-bike ridership, which may suggest that the distribution of the number of docking slots at some stations was not quite reasonable and the e-BSS managers may want to adjust it. Furthermore, the regression results show that 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. Future planners may use this finding as a reference for the deployment of bike share stations.

Overall, this study presented the e-bike share experience in Park City and provided useful information for the planning of future e-bike share systems. The current study was limited to the information available in the e-bike usage data; we lacked user demographic information (e.g., users' income information was unknown, and only members provided their gender information). In future research, it is worth exploring the socioeconomic factors that may affect e-bike share usage.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Yi He, Ziqi Song, Zhaocai Liu; data collection: Yi He, Zhaocai Liu; analysis and interpretation of results: Yi He, Zhaocai Liu, Ziqi Song, N. N. Sze; draft manuscript preparation: Yi He, Zhaocai Liu. All authors reviewed the results and approved the final version of the manuscript.

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LIST OF FIGURES

TABLE 1 Trip Distribution among Stations

(a) Regular User

Origin \ Destination	KJTC	NP	CTH	PN	PCL	OTTC	CC	TO	DVRS
KJTC	137	42	20	5	11	26	6	5	26
NP	6	361	31	3	9	24	4	7	25
CTH	18	33	264	5	19	37	0	6	49
PN	0	0	0	13	0	0	0	0	0
PCL	9	13	22	14	190	46	0	0	33
OTTC	8	18	37	8	30	111	0	3	52
CC	0	0	1	0	0	0	4	0	0
TO	0	2	0	0	0	0	1	0	0
DVRS	9	11	8	1	20	31	0	0	142

(b) Non-regular User

Origin \ Destination	KJTC	NP	CTH	PN	PCL	OTTC	CC	TO	DVRS
KJTC	125	84	25	9	10	19	9	16	29
NP	74	686	78	19	26	60	10	17	47
CTH	28	52	405	19	20	108	2	11	88
PN	7	34	33	415	67	112	1	3	70
PCL	7	13	31	57	188	116	1	5	61
OTTC	27	50	95	116	117	414	1	6	163
CC	9	15	4	3	1	6	44	3	7
TO	17	18	13	2	1	3	5	53	2
DVRS	32	80	90	107	75	170	3	3	543

Note: KJTC represents Kimball Junction Transit Center, NP represents Newpark Plaza, CTH represents Canyon Transit Hub, PCL represents Park City Library, OTTC represents Old Town Transit Center, CC represents Canyon Corners, TO represents Tanger Outlets, DVRS represents Deer Valley Resort Station.

TABLE 2 Regression Results

Variable	Aggregate Ridership Model			Regular User Model			Non-regular User Model		
	Parameter Estimate	Standard Error	Pr > ChiSq	Parameter Estimate	Standard Error	Pr > ChiSq	Parameter Estimate	Standard Error	Pr > ChiSq
Intercept	-1.0340	0.8474	0.2224	-3.1925	1.2260	0.0092**	-1.1577	0.8994	0.1980
AveTemp	0.0308	0.0038	<.0001**	0.0311	0.0059	<.0001**	0.0309	0.0040	<.0001**
Visibility	0.0239	0.0753	0.7511	0.0593	0.1078	0.5821	0.0170	0.0801	0.8350
WindSpeed	-0.0868	0.0379	0.0218*	-0.2171	0.0574	0.0002**	-0.0638	0.0398	0.1085
PrecipAmo	-0.0642	0.1175	0.5850	-0.1051	0.1686	0.5331	-0.0556	0.1249	0.6563
DayType	-0.4136	0.0554	<.0001**	0.0129	0.0856	0.8806	-0.4865	0.0584	<.0001**
Summer	0.5005	0.0856	<.0001**	0.6859	0.1298	<.0001**	0.4672	0.0901	<.0001**
Capacity	-0.0107	0.0121	0.3801	-0.0238	0.0167	0.1537	-0.0081	0.0130	0.5356
TransitCen	1.6455	0.1637	<.0001**	1.7975	0.2258	<.0001**	1.6143	0.1751	<.0001**
RecrCen	1.1484	0.1161	<.0001**	0.9315	0.1706	<.0001**	1.1826	0.1229	<.0001**
BikeTrail	0.3951	0.0861	<.0001**	0.5538	0.1313	<.0001**	0.3697	0.0905	<.0001**
Population	0.0029	0.0002	<.0001**	0.0029	0.0003	<.0001**	0.0029	0.0002	<.0001**
Scaled Deviance/DF	1.0000			1.0000			1.0000		
Scaled Pearson Chi-Square/DF	1.1300			1.2821			1.1522		

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

Figure 1

Click here to access/download;Figure;FIGURE 1.png

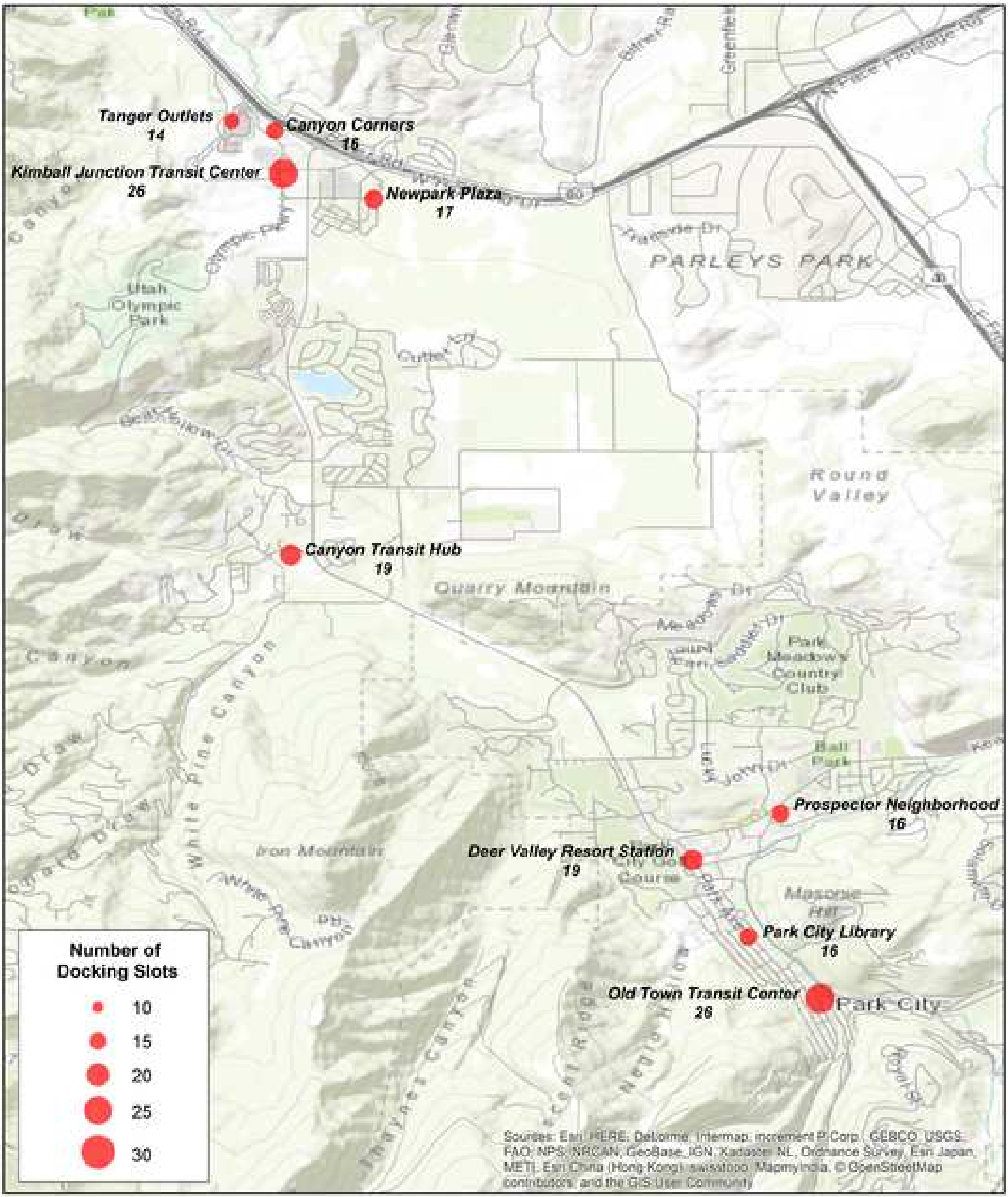
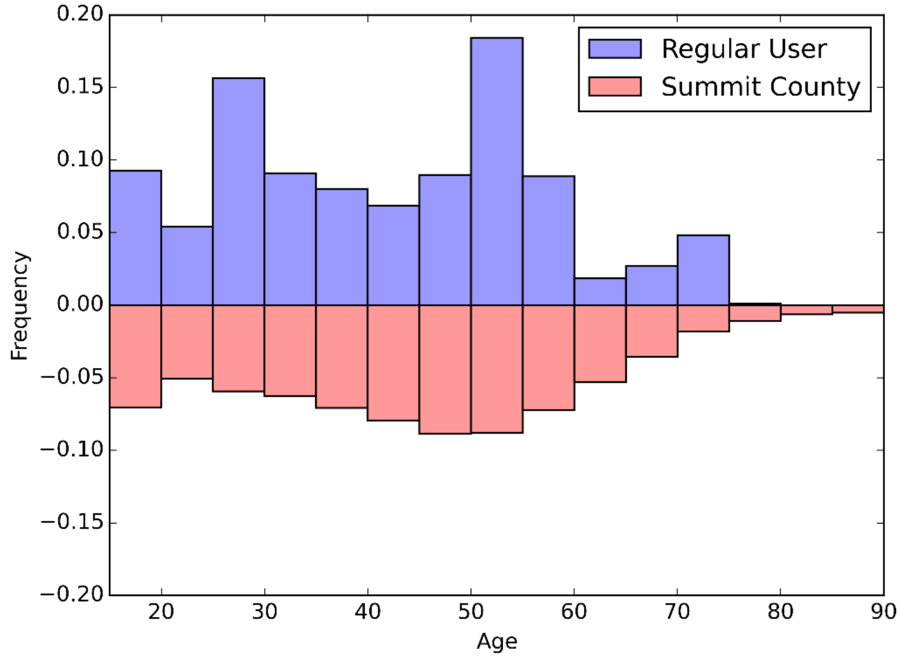
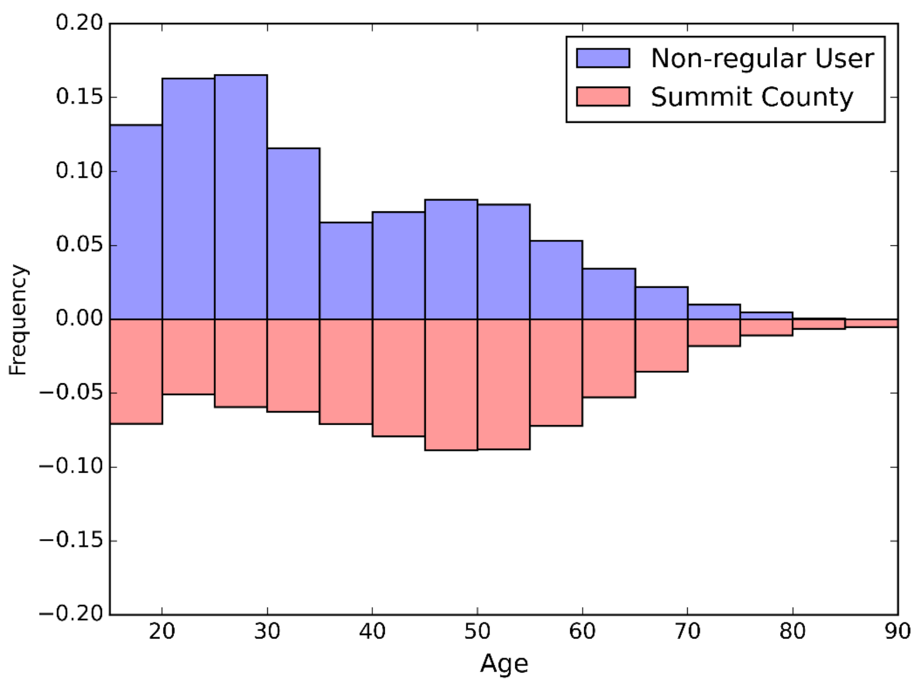


Figure 2 Click here to access/download;Figure;FIGURE 2.jpg

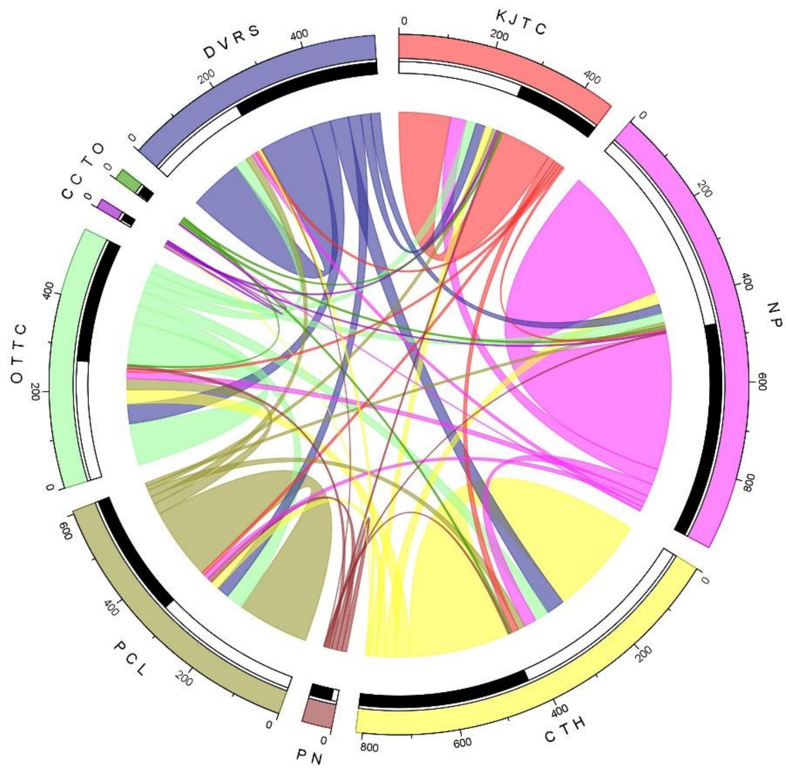
Figure 3



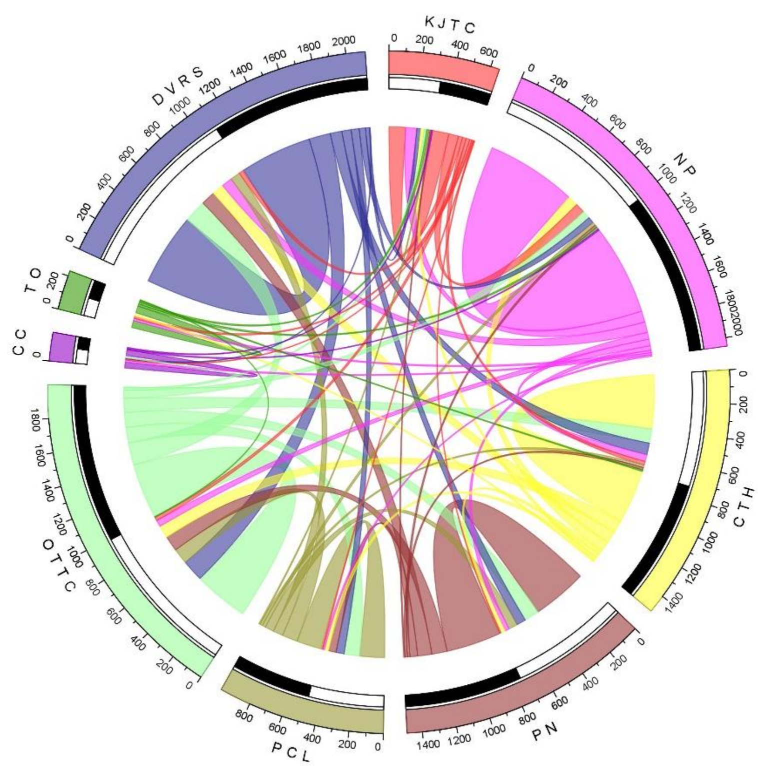
(a) Regular user



(b) Non-Regular user

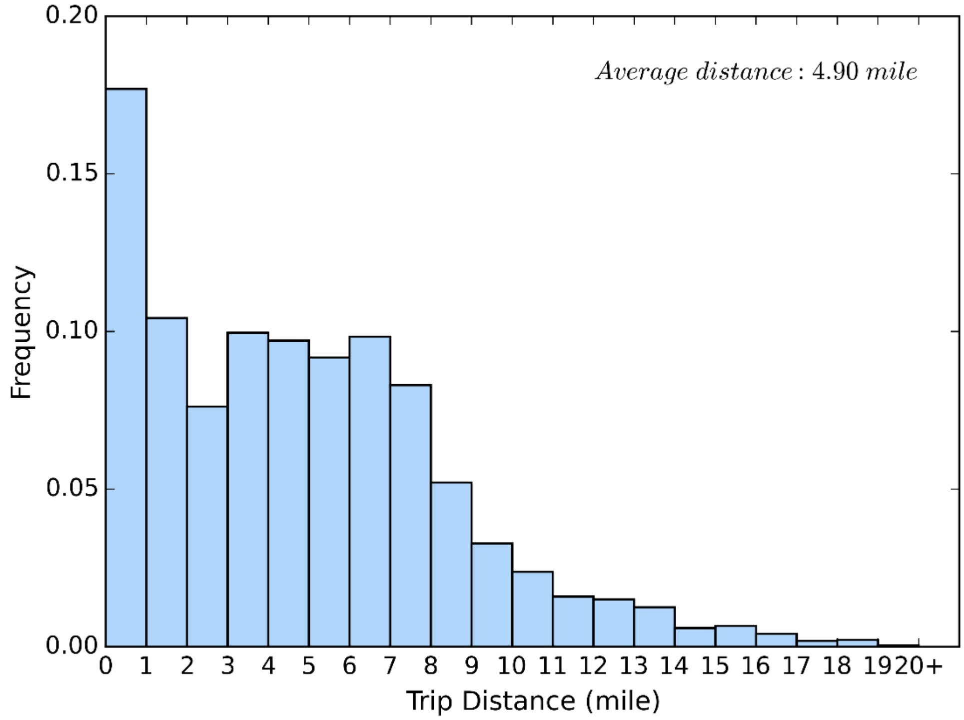


(a) Regular user

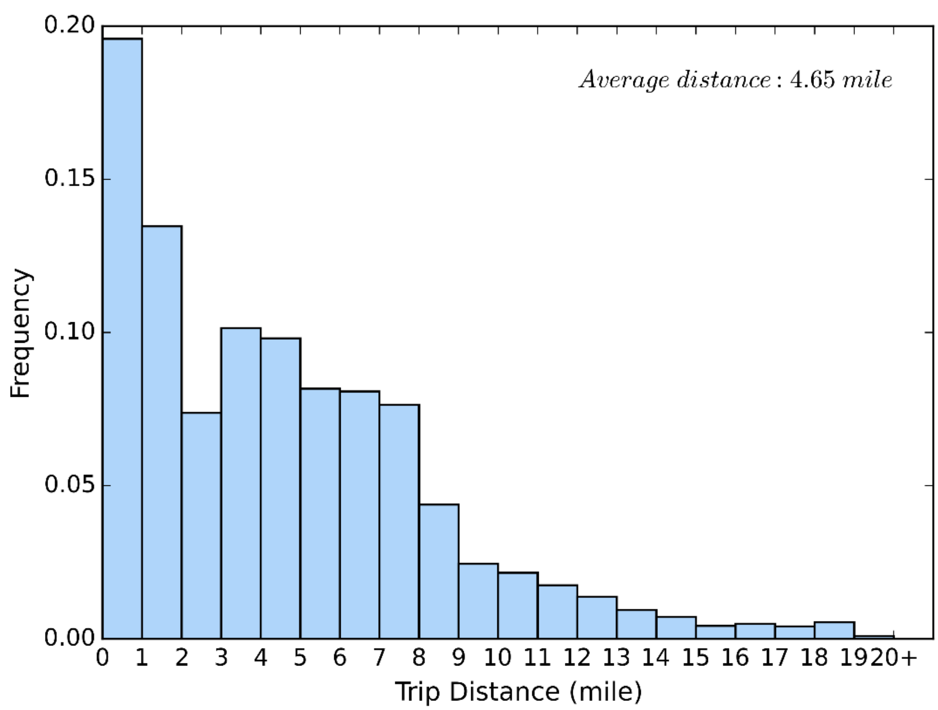


(b) Non-Regular user

Figure 5



(a) Regular user



(b) Non-Regular user

Figure 6

Click here to access/download;Figure;FIGURE 6.png