



FINAL REPORT

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E-Bikes' Effect on Mode and Route Choice: A Case Study of Richmond, VA Bike Share

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16. Abstract The bicycle has become a legitimate transportation option in many cities due to its different benefits. Lower transportation costs, health improvement, and lower emission rates are some critical benefits of a bicycle ride. A large body of research exists on bicycle route choice and travel behavior. There is currently a lack of research on mode shift and route choice changes with the introduction of e-bikes. This study has presented a comprehensive analysis of the similarities and differences between a pedelec and regular bicycle use in Richmond City, Virginia, as well as an evaluation of how membership type and other user characteristics might influence bike share use. This study utilized GPS data for a docked bike-share system in Richmond, Virginia, from March 2019, when RVA Bike Share began converting the traditional bikes to e-bikes. To retrieve the data this study used Mapbox's Map Matching API, which snaps fuzzy, inaccurate GPS traces to actual segments in the road network, breaks the snapped roads into segments and queries each segment in Open Street Maps (OSM) to identify the type of road. This study did a comprehensive descriptive analysis, origin-destination trip analysis, and user cluster analysis with the retrieved data. The results have shown that pedelecs are generally associated with longer trip distances, shorter trip times, higher speeds and lower elevations. In April, about 25% of the fleet was pedelec bikes and by December, approximately 65%. The t-tests results showed that the mean number of trips made per bike available was significantly more (~3.2x) for pedelecs compared to bikes (p-value=0.004). The origin-destination analysis considered the business, mixed use, residential and other uses and observed that the plots show extremely similar trends with a large number of trips staying within either business or residential locations or mixed use. The roadway use analysis and mapping showed that pedelecs were used farther outside of the city than bikes. Additionally, pedelecs were frequently used in the downtown core where most RVA bike share stations are located. In terms of memberships, longer-term memberships (annual, monthly) were found to be associated with significantly higher use of pedelecs than shorter-term memberships, potentially pointing to a lack of knowledge on the part of those who use the system less frequently or to a preference for normal bicycles. Finally, the user cluster analysis identified six diverse types of behaviors that varied by geographical region (e.g., central Richmond vs. recreational areas), as well as by trip distance, trip duration, and bike type.			
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INTRODUCTION

The bicycle has become a legitimate transportation option in many cities due to its many benefits. Lower transportation costs, health improvement, and lower emission rates are some critical benefits of a bike ride. In congested cities, cycling is an efficient mode of transportation. Global climate change and energy security concerns are also growing, reflected in the sustainable transport system. Bike sharing – a service in which bikes are made available to the public, sometimes for a fee – is growing worldwide to keep pace with these growing concerns. Public bike share programs offer a solution to short trips and, through integration with public transit, serve as a first- and last-mile solution. People consider bike share a greener and better way of life [1]. However, due to users' age and different health conditions, and local areas' infrastructure and terrain, some people cannot regularly use a bicycle. Electrically assisted bikes (e-bikes) are being introduced in many western countries to overcome these issues. The introduction of e-bikes has reduced traditional all-human powered cycling barriers, including the perception of fitness needed, age, terrain condition, and travel speed [2-5].

A large body of research exists on bicycle route choice and travel behavior. GPS data provides researchers with the opportunity to analyze route choice decisions as a function of built environment characteristics. Bicycle route choice involves the joint consideration of convenience, safety, and leisure [6]. Several studies have found that cyclists prefer facilities on flat, low-volume roads with slow traffic or separated bike infrastructure [6, 7]. This research has been used to develop level of traffic stress measurements [8-11], determine the location of bicycle infrastructure [12-15], and provide route guidance [11, 16, 17] as a function of traffic volumes, speeds and bike infrastructure provision.

Currently research is lacking on mode shift and route choice changes with the introduction of e-bikes. As shown earlier, e-bikes remove some biking barriers associated with health and physical ability. Physical ability is linked to route choice factors, such as route length and terrain [18]. Additionally, e-bikes may influence safety-related factors such as traffic speed and perceived safety at stops [19]. Studies have found that route choice varies by age and gender [12, 20, 21]. A study of Baltimore's bike share found that less-educated, lower-income, nonwhites and females were underrepresented in Baltimore's bike share. Of those underrepresented communities, gender was the only significant barrier. Females express concern over specific barriers to accessing and using bike share, including how to use the system, personal safety, helmet use, harassment, and hygiene [12]. By allowing quicker acceleration and reducing the speed differential between bikes and vehicles at upgrades, e-bikes may influence modal and route choice decisions. A comparative study of e-bikers' route choice would explore the impact e-bikes have on cycling trip characteristics and route choice. In this study, we determine if the adoption of e-bikes changed the quantity and length of Richmond, Virginia, (RVA) bike share trips and how route choice decisions change with the introduction of e-bikes.

LITERATURE REVIEW

Bike Share Programs

Introduced by transportation planners and often called rental bikes or public use bicycle programs, bike share programs have been implemented worldwide [17]. There are many bike sharing systems, with public bicycle sharing and recreational bicycle-sharing systems being the most common. Universities have introduced bike share programs exclusive to their students for commuting on campus. The majority of public bicycle sharing systems in urban settings aim to give commuters an accessible and time-efficient transportation mode in congested areas. Different business groups (Bewegen, Copr, CycleHop, Citi Bike, Lime bike, and many more) operate bicycle rental programs. Users can rent both docked and dockless bicycles depending on their origin and destinations and bike share companies' systems. People can also rent for a few hours or for a few days, depending on their needs. Bike-sharing programs allow participants to use a bicycle as needed without bicycle ownership costs and responsibilities [23].

The first bike sharing program was introduced in Europe in 1965 when the “white bike plan” was launched in Amsterdam, so named because its few bikes were painted white. In the first-generation bike share, the bikes were placed in various locations around the town for free use. The program suffered from stolen and damaged bike problems, and eventually the plan collapsed. The second-generation bike share program was a coin-operated system first launched in Copenhagen, Denmark, in 1995. It was hoped that this system would resolve the theft problem that the first-generation bike share faced. In 1996, the cities of Minneapolis and St. Paul in Minnesota also started a bike share program. In this program, people put in a coin to unlock the bike from the bike rack to use it. However, there was no system to identify the users, which led to a prevalence of stolen bikes [24].

Third-generation bike share programs have greatly minimized issues of theft. Bike-sharing applications now use different technologies, including smartphone use, GPS tracking, debit/credit card payment systems, real-time bike inventories, and many more to track the bike and user's route to prevent theft, creating an incentive to bring the bikes back promptly [24]. More than 1,000 cities have a bike sharing program, and the numbers are increasing. In China, Hangzhou has the world's most extensive bike-sharing program, well integrated with other public transport forms. In the USA, bike sharing is also increasing in popularity, with both docked and dockless bikes shares popular among rider groups. In 2016, the total number of bike share bikes was 42,500, which doubled in 2017 to 100,000 bikes. In 2017, dockless bike share companies added almost 44,000 bikes worldwide, while 14,000 station-based bikes were added to the system [25].

Introduction of E-bikes

An electric bike or e-bike is a bicycle that has an electric motor that provides power assistance up to speeds of 25 km/hour. This kind of bike is engaged with a throttle grip or pedaling and has a power output of 250 W, and power can only be engaged by pedaling, also called pedal-assist or pedelec [2]. E-bikes are an excellent addition to bike share programs since they reduce many barriers to pedal

cycling such as age issues, health issues, steep terrain, lack of time, and end-of-tour facilities [2-5]. Most e-bikes look similar to conventional pedal bicycles and have their battery pack fitted in a different location such as the seat post, bike frame, or rear rack [26]. Though the power assistance makes the riding more comfortable, users still need to pedal, which provides physical activity benefits [27]. E-bikes are attractive to people with injuries, or those who are less fit or older.

Due to the many benefits, e-bikes are becoming more common in different countries. In Europe, many countries' e-bikes account for 12% to 15% of total bicycle sales [28, 29]. Europe has also seen a significant increase in e-bikes sales [30]. Different studies show that e-bike access increases the number and distance of bike trips [31, 32]. E-bikes are also energy efficient and environmentally preferred modes compared to other motorized transportation modes [33]. An e-bike is also quicker than a traditional bicycle and enables users to take longer trips, even on hilly routes. E-bikes also can replace many car or bus trips and avoid rush hour traffic by offering competitive travel speeds.

Factors affecting Route Choice for Bicycle and E-bike Users

The route choice decision of any bicyclist is a difficult and challenging issue. Many factors influence the attractiveness of different routes, and different studies have been conducted to understand the attributes that affect route choice decisions.

Campbell et al. (2016) did a mode choice survey and used the data to develop a multinomial logit model for mode choice to evaluate the factors influencing the decision to switch from an existing transportation mode to bike share or e-bike share in Beijing. The modeling result shows e-bike share riders give less importance to the distance of the trip, temperature, and low air quality than do traditional bike riders, for whom precipitation plays a negative role. The result also shows that the e-bike share provides an attractive alternative to the bus [34]. Khatri et al. (2016) used GPS data from 1,866 bicycle users in Phoenix, Arizona, who were enrolled in a bike share program called Grid Bike share. This bike share system had a unique feature that allowed users to drop the bicycle away from the station for a small extra fee. This study compared two types of users: registered users and casual users. The researchers cleaned the GPS data and matched it to the road network. A path size logit model was used to understand route choice, and the result shows riders use a more bike-friendly environment rather than the shortest path. Most registered users preferred cycling on lower volume and lower speed roads than casual users. The magnitude of the coefficient also shows that registered users are more sensitive to route length than occasional users. Again, different facilities such as bike lanes, multi-use paths, or share paths have more acceptance. Travel on the bike-specific facilities was equivalent to a decrease in the distance by 44.9% compared to 53.9% for casual users [33].

Hood, Sall, and Charlton (2013) tried to recognize cyclists' decision-making by using a route choice model. The model is run with GPS data of bicycle users' smartphones in San Francisco through a free application called CycleTracks. The path size logit route choice model result estimated that cyclists in San Francisco highly prefer bike lanes to other bicycle facilities. The result also showed that bicyclists avoid route that require climbing hills, turning, and deviating excessively from the minimum distance paths [35]. Stinson and Bhat (2003) analyzed 11 determinants of route choice decisions from a stated preference survey data by a discrete-choice modeling framework. The survey questionnaire, conducted

online, is designed using a series of hypothetical route choice questions to understand the user's route choice. The evaluation of route level and link level factors revealed that travel time is a significant factor behind choosing any route. Other highly essential elements are bicycle facilities along any road or bridge, riding surface quality, and automobile traffic level [36].

Broach, Gliebe, and Dill (2009) did a survey evaluation study in Portland, Oregon. They used detailed survey data of 150 bicyclists using GPS tracking devices to reveal the actual paths. The authors used GIS mapping of the street network and off-street way with all the attribute information regarding facility types, daily vehicular traffic volumes, and elevations. The result of the route choice model, which was formulated as a path size logit model, indicates that users are more concerned about total path length. Turns across heavily traveled arterials and high-traffic-volume through streets without separate bike facilities play a negative role in route choice [37]. Segadilha and Sanches (2014) did a survey study to understand bike users' route choices. The study was carried out in Brazil among 65 cyclists. Eighteen factors were grouped into five categories: characteristics of road, traffic, environment, trip, and route. The bicyclists also used a GPS device, and the result is obtained through GIS analysis. The results show that motor vehicle speed and the number of trucks on the road play a crucial factor in route choice. Other essential elements are the number of motor vehicles, street lighting, and security [38]. Using a web-based stated preference survey of Texas bicyclists, Sener, Eluru, and Bhat (2009) studied and evaluated the attributes that influence bicyclists' route choice decisions. The study evaluates a comprehensive set of characteristics, including bicyclists' factors, on-street parking facilities, bicycle facilities, and roadway physical, functional and operational features. The mixed multinomial logit model analysis shows that the motorized vehicle's travel time and volume are the most crucial attributes in route choice decisions. Other relevant factors are cross streets, red lights, speed limit, and bicycle facilities [39].

Impacts on Travel Behavior and Mode Choice

Introducing e-bikes in any city influences the travel behavior of the e-bike riders. One Norwegian study had 66 individual e-bike users compared with a control group of 160 individuals. The results show that due to the e-bike introduction, the cycling trip increased from 0.9 days to 1.4 days. The riding distance also increased from 4.8 km to 10.5 km while the control group showed no increase. The proportion of trips by e-bike also increased from 28% to 48% [32]. A study done by MacArthur et al. (2014) tried to answer two questions: Will e-bikes get more people to ride and will e-bikes increase riding frequency? They found that e-bikes may increase cycling participation, and almost 55% of people start riding daily after getting e-bikes while 93% ride weekly [3]. Langford et al. (2013), used e-bike share data from North America's first e-bikesharing system (cycleUshare), at the University of Tennessee, Knoxville. The study found that 22% of users accounted for almost 81% of bike trips. Speed and comfort play a vital role in selecting an e-bike instead of a regular bicycle. The bike share expanded user mobility and reasons of trip purposes. E-bike riders rode 13% farther than their conventional bike share counterparts [40]. Some other studies also show that e-bike users travel a greater distance than traditional bicycle users. Another study by Cherry et al. found that the distance traveled by e-bike increased 4 km between 2006 to 2012 [41]. One study in two Chinese cities showed that the increased use of e-bikes also improved the vehicle kilometer traveled (VKT), by 9% and 22%

in Shanghai and Kuming, respectively. The travel speed is even higher for e-bikes than traditional bikes, 15% in Shanghai and 10% in Kuming [42]. Different studies also figured out riders' mode choice behavior with the increased use of e-bikes. Cherry et al. (2014) show in their research that almost 25% of e-bike riders alter their car-based rides and 60% replace their bus trips with an e-bike [41]. Another study by Langford et al. (2013) also showed that the e-bike displaced 11% of car trips in the respected study area [40]. In Macartur et al.'s (2014) study, 65% of respondents want to use e-bikes to replace car rides [3]. Johnson and Rose (2013) studied Australia via an online survey to understand the e-bike owners' decision-making process. The study found that 60% of the respondents' motivation for purchasing an e-bike was to cut out some car trips [43].

Previous studies focused on the factors behind using e-bikes and their influence on mode choices. Several studies relied heavily on surveys to determine differences between bike and e-bike use. This study will utilize GPS data for a docked bike-share system in Richmond, Virginia, to determine if the adoption of e-bikes changed the quantity and length of bike share trips and how route choice decisions change with the introduction of e-bikes.

DATA COLLECTION AND STUDY DESIGN

Study Site: RVA Bike Share

In 2017, Richmond, Virginia, launched the RVA Bike Share. At its launch, the system offered only traditional pedal bikes. Beginning in March 2019, RVA Bike Share began converting the traditional bikes to e-bikes. Currently, a total of 220 bikes (both traditional and pedelec) are available across 19 stations throughout central Richmond, Virginia. At the time of the study the Downtown YMCA station was open and Main Street Station was not yet in operation.

There are six general pricing structures for the RVA Bike Share. Bike share trips can be charged per trip (Go Pass and One-way Trip Pass) or people can pay to take an unlimited number of trips within a year, month, week, or day. Trips over 45 minutes are subject to overage fees of \$3 per 30 minutes. Figure 1 shows the locations of the RVA Bike Share stations in relation to the bicycle facilities. During the study period two special memberships were offered. The Fall Offer Pass was offered from October to December and the RVA Mural Bike Tour occurred in August.

Table 1: RVA Bike Share Membership Categories

Membership	Description	Price
Annual	Unlimited 45-min rides for 1 year. 1 bike per membership.	\$96
Monthly	Unlimited 45-min rides for 1 month. 1 bike per membership.	\$18
Weekly Pass	Unlimited 45-min rides for 7 days. One bike per pass, possible to purchase up to 4 passes at the kiosk.	\$12
Day Pass	Unlimited 45-min rides for 24 hours. One bike per pass, possible to purchase up to 4 passes at the kiosk.	\$6
Go Pass	Receive a pass to unlock bikes but pay per 45-min ride. Not available at kiosk.	\$1.75 per ride
One-way Trip Pass	One 45-min ride. A pass is dispensed at the kiosk to unlock the bike. May rent up 4 bikes at once.	\$1.75 per ride

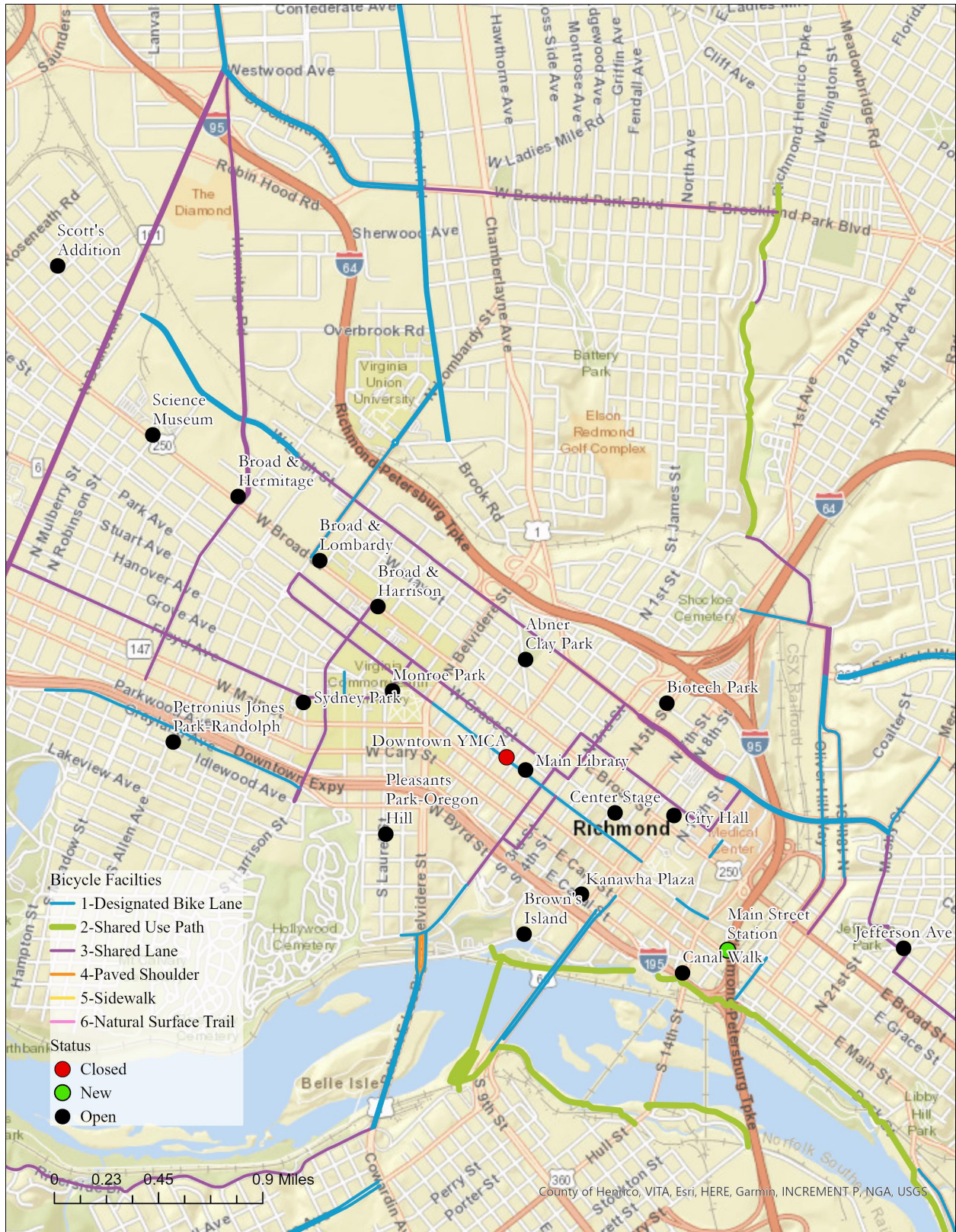


Figure 1: RVA Bike Share System

Trip Data

RVA Bike Share data was received from the bike share operator Bewegen. The dataset contained a total of 4,075 trips collected during the first week of each month from April 2019 to December 2019. The data contained the following information:

- Bike unlock date
- Bike unlock time
- Bike lock date
- Bike lock time
- Membership type
- Distance (in miles)
- Duration (in minutes)
- Bike ID
- Type of Bike (bike or pedelec)
- Cost of trip
- Start station
- End station
- Route ID
- User ID

Trips shorter than 30 seconds, longer than 3 hours and trips that covered more than 100 km (62 mi) were filtered out to eliminate outliers from the dataset that could be related to incorrect system performance or to people simply trying out the bicycles but not traveling. The total final number of trips was 3,519 with 2,257 pedelec trips and 1,262 traditional bicycle trips. Figure 2 shows the total number of trips that started and ended at each station, and Table 2 presents the number of trips which started and ended at each station during the study period.

Table 2: Number of Trips Originating and Destined to Each Station

Station	Origin	Destination	Total
Abner Clay Park	120	111	231
Biotech Park	34	40	74
Broad & Harrison	308	258	566
Broad & Hermitage	0	3	3
Broad & Lombardy	216	218	434
Brown's Island	569	639	1208
Canal Walk	455	466	921
Center Stage	210	176	386
City Hall	93	73	166
Downtown YMCA	0	1	133
Jefferson Ave	132	134	247
Kanawha Plaza	113	106	145
Main Library	39	47	610
Monroe Park	563	602	724
Petronius Jones Park-Randolph	122	137	314
Pleasants Park-Oregon Hill	177	148	277
Science Museum	129	104	185
Scott's Addition	81	83	241
Sydney Park	158	173	173

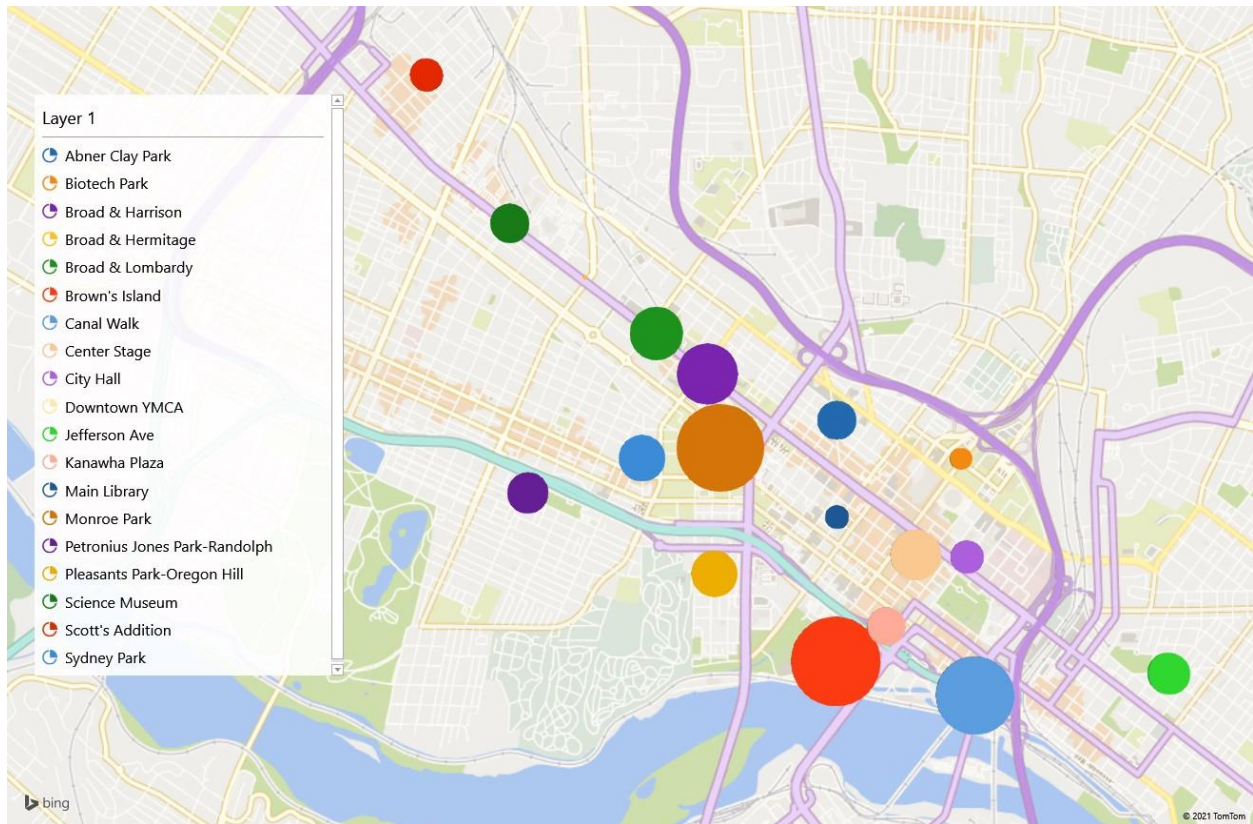


Figure 2: Total Number of Trips to and From Station (min = 3 trips, max = 1208)

Data Summary

RVA Bike Share began to transition pedelecs into the system in March 2019. As more e-bikes were introduced into the fleet, the percentage of trips by pedelec increased (Figure 3). By December 2020 the fleet of pedelec bikes was roughly 65%, but over 90% of trips were taken on a pedelec bike.

Figure 4 shows the number of trips made each month. The busiest days were Sunday (represented by =1) and Saturday (=7). More trips were made on Friday than other weekdays. Figure 5 shows the total number of trips made by hour of the day by on the weekday and weekend. The busiest time period for RVA bike share on the weekend is between 2 pm and 7 pm, and on the weekdays it's 4 pm to 6 pm following workday peak trends. Morning bike share use was more prevalent on the weekdays, capturing people who use the bike share for commuting.

Trips were categorized into two categories. Touring trips are trips that start and end at the same station and O-D trips have a different origin and destination. As shown in Figure 6, the morning trips are dominated by O-D trips, likely commuting trips. Figure 7 shows the total number of O-D and touring trips by the origin station. Brown's Island, Canal Walk, and Monroe Park, which have recreational land use, have the highest number of trips. Several of the downtown stations such as Brown & Harrison and Center Stage had more O-D trips compared to touring trips.

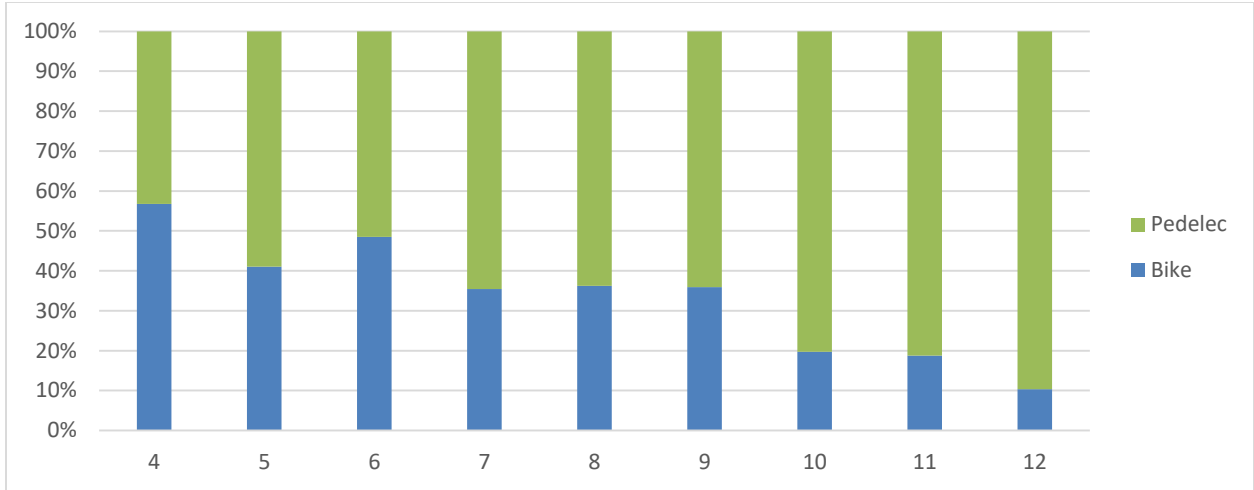


Figure 3: Percentage of Trips by Bike Type Per Month

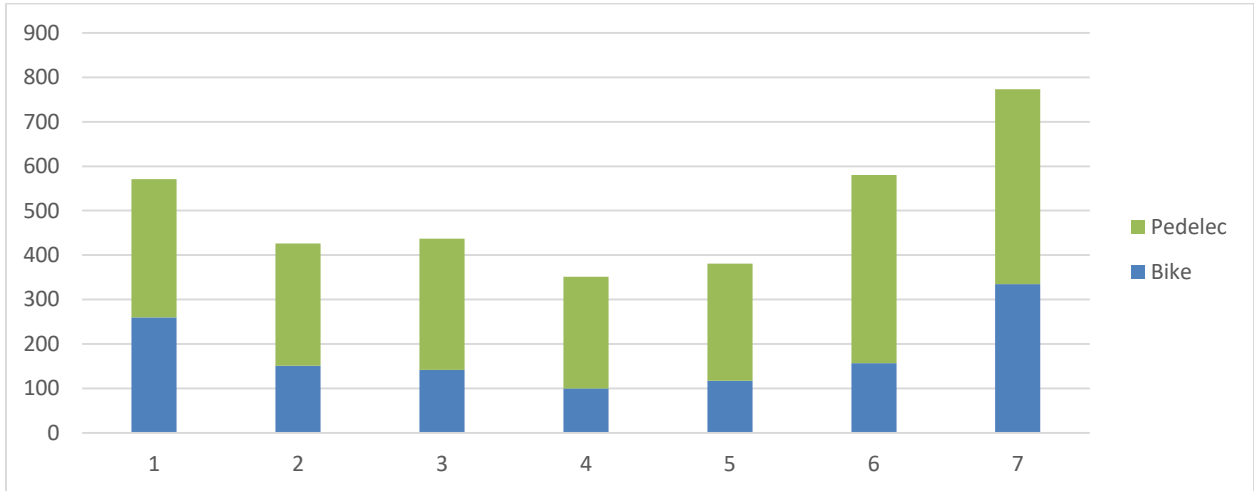


Figure 4: Total Number of Trips per Week (1= Sunday, 7=Saturday)

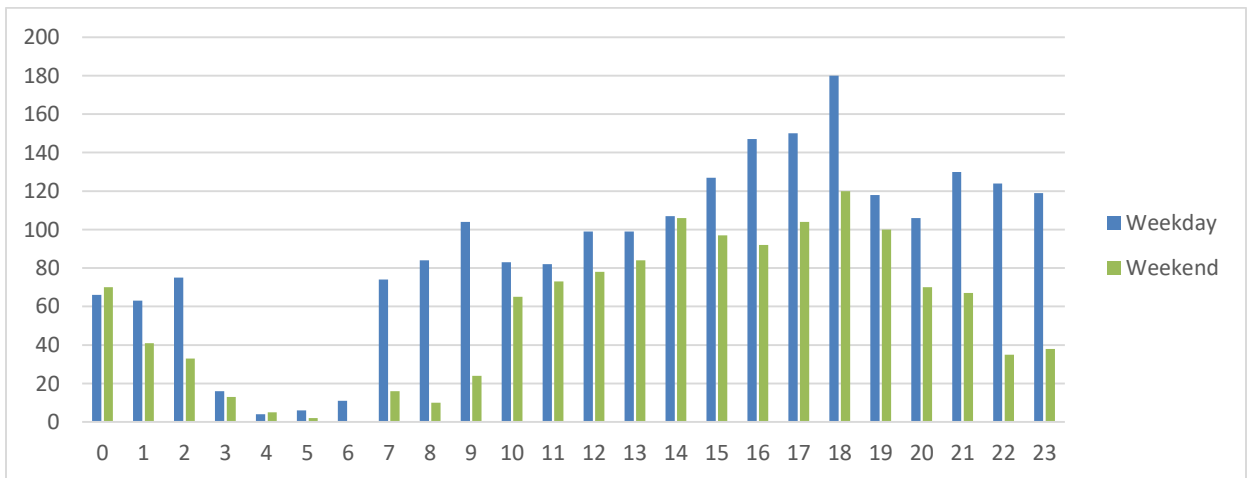


Figure 5: Total Number of Trips per Hour of the Day (Weekday vs. Weekend)

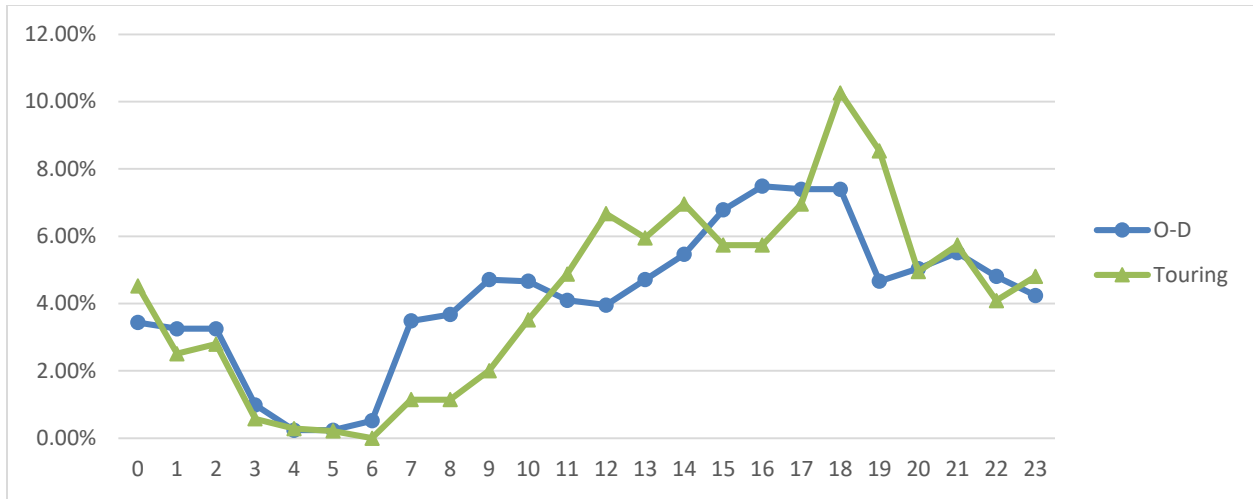


Figure 6: Percentage of Trips by Time of Day: Touring vs. O-D

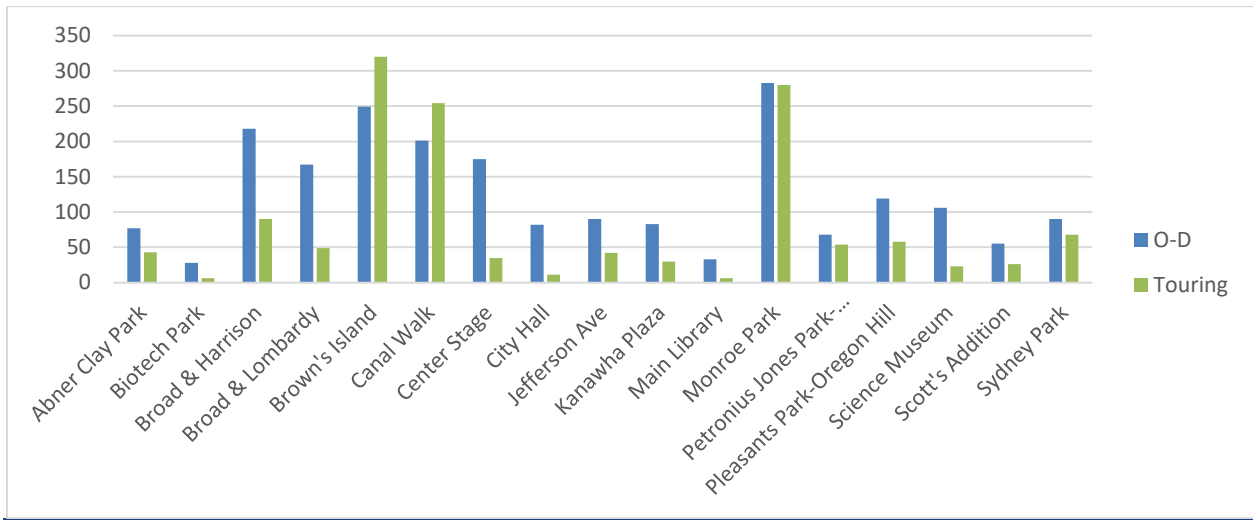


Figure 7: Total Number of Trips Originating from Each Station: O-D vs. Touring Trips

Membership Types

Over the study period, the majority of trips (75%) were made by those who paid by the ride (go passes and one-way trip passes). Annual, monthly, and weekly membership trips were only 14% of all trips; see Figure 9. Subscription members had the highest rates of trips made by pedelecs; whereas one-way trip passes, day passes, and go passes had the lowest rate of pedelec use; see Figure 10: Percent of Trips made on Pedelecs and Bikes by Membership Type. It is not clear if the difference in pedelec use reflects differences in trip purposes or familiarity with the system. Pedelecs are identified by a lightning bolt on the back of the bike. As shown in Figure 11, annual members (and other subscription members) take more trips that have a different start and end station (O-D trips) while short-term members and pay per trip riders tend to take more trips that start and end at the same station (touring trips).



Figure 8: Photo of Pedelec Bike (Source: RVA Bike Share)

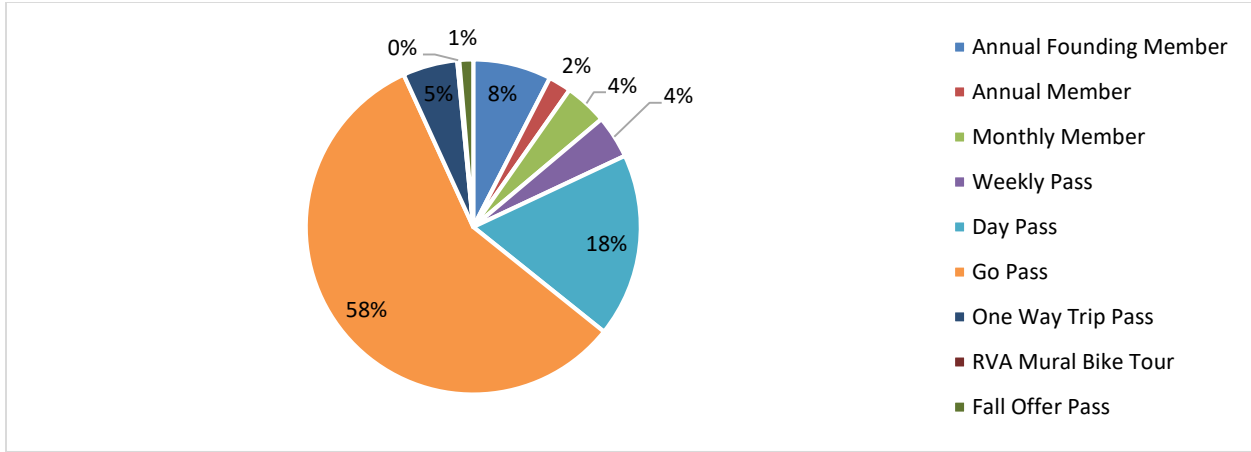


Figure 9: Percent of Trips by Membership Type

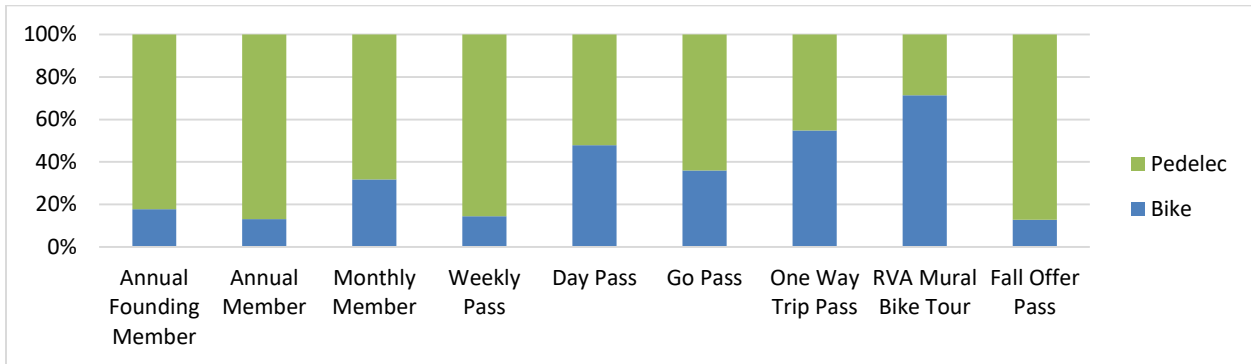


Figure 10: Percent of Trips made on Pedelects and Bikes by Membership Type

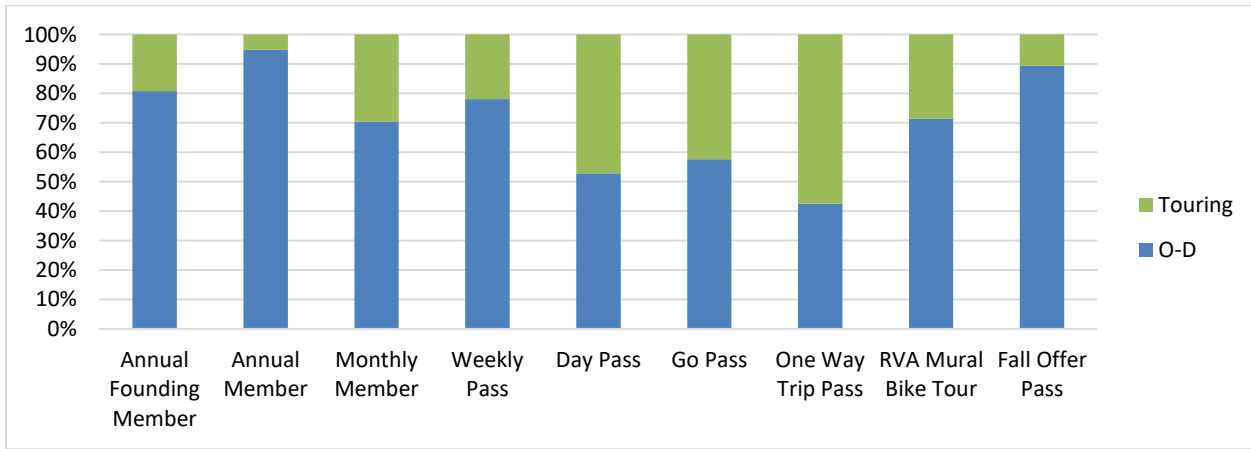


Figure 11: Percent of Trips Touring vs. O-D by Membership Type

On average O-D trips were about 2.3 miles and touring trips 3.4 miles; see Table 3. Annual founding members had the largest difference in the average miles of O-D (2.0 mi) and touring (5.0 mi) miles. RVA Mural Bike Tour trips had the longest travel time at 92 minutes. On average, touring trips were about twice as long as O-D trips (45 mins vs. 24 mins).

Membership Type	Average Distance (mi)			Average Time (min)		
	O-D	Touring	All Trips	O-D	Touring	All Trips
Annual Founding Member	2.0	5.0	2.6	14.1	34.8	18.1
Annual Member	1.0	1.0	1.0	7.6	14.6	8.0
Monthly Members	2.6	3.4	3.0	32.5	48.2	39.9
Weekly Pass	2.3	3.5	2.8	26.3	46.6	34.9
Day Pass	1.1	2.1	1.4	10.9	29.9	16.5
Go Pass	2.3	2.9	2.7	25.7	37.3	32.4
One Way Trip Pass	3.2	3.7	3.3	25.4	35.6	27.6
RVA Mural Bike Tour	6.6	0.8	5.0	92.0	18.2	70.9
Fall Offer Pass	1.6	2.6	1.7	13.1	24.9	14.3
Grand Total	2.3	3.4	2.7	24.4	44.8	32.5

Research Questions

The descriptive analysis of RVA Bike Share data showed that pedelec bikes were preferred over traditional bikes. There were differences in use across membership types and trip types. The rest of the study looks at a subset of trips to answer the following questions:

- RQ1. Are there significant differences in trip characteristics based on bike type?
- RQ2. How does membership type and other user characteristics influence bike share use?

To answer the questions above, we matched the GPS data from each of the trips to the roadways and plotted all the trips for each user group cluster (see Figure 25).

Methodology

Retrieving the street segments associated with the GPS traces of a cycling trip is not straightforward since GPS sensors have errors, and more so in urban environments where, when surrounded by tall buildings, the GPS might lose the signal or record a location quite far away from the actual one. As a result, we retrieved the list of street segments cycled using Mapbox's Map Matching API, which snaps fuzzy, inaccurate GPS traces to actual segments in the road network [44]. Internally, Mapbox uses the map-matching algorithm by Newson and Krumm, based on Hidden Markov Models (HMM), that find the most likely street segment in the network that is represented by the collected GPS location [45]. We then break the snapped roads into segments and query each segment in Open Street Maps (OSM) to identify the type of road.

RQ1. DIFFERENCES IN PEDELEC AND BIKE TRIPS

Using all trips, we gathered the number of unique bikes used in a given month to estimate the number of bikes and pedelecs available. In April, about 25% of the fleet was pedelec bikes and by December approximately 65%; see Figure 13. Figure 12 shows the rate of trips made per available bike. T-tests results showed that the mean number of trips made per bike available was significantly more (~3.2x) for pedelecs compared to bikes (p-value=0.004).

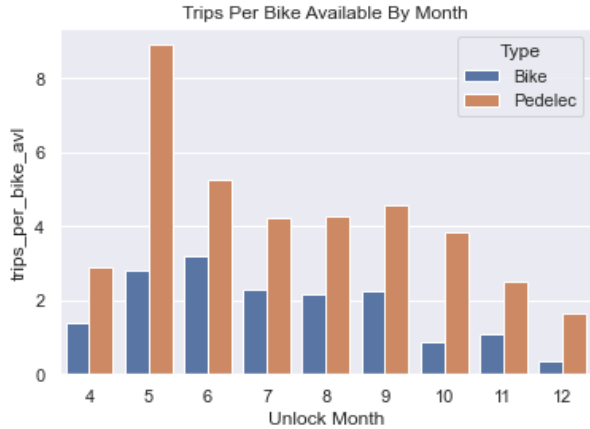


Figure 12: Number of Trips Made Per Available Bike or Pedelec

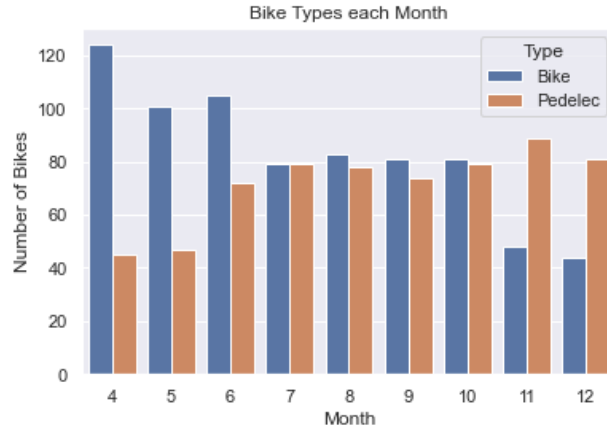


Figure 13: Number of Bikes and Pedelecs Available Per Month

Table 4: Use Differences between Pedelecs and Bikes Considering All Trips

Variable	Pedelec Mean (N=2259)	Bicycle Mean (N=1263)	p-value
Total Distance (mile)	2.91	2.39	6.51E-11
Rate of Elevation Change (ft/ft)	0.00762	0.00876	6.81E-08
Trip Time (min)	30.7	35.3	2.12E-05
Total Speed (mph)	6.5	4.7	6.04E-93

We first analyzed the differences in the use of pedelecs and non-electric bicycles in Richmond, Virginia, for the period under analysis (nine months). For that purpose, we divided all the trips into pedelec and bicycle trips and retrieved trip length, trip duration, speed, and elevation values for all the trips in each group. Elevation was computed only counting uphill, although the analysis with uphill and downhill values gave similar results. To evaluate if the differences between these use variables across pedelec and bicycle trips were statistically significant, we ran t-tests between each pair of distributions. Table 4 shows the mean values for each of the use variables and the p-value associated with the statistical significance test. We can observe that pedelecs are associated with longer trip distances, shorter trips times, and higher speeds. These results highlight the fact that pedelecs are faster (6.5 mph vs. 4.7 mph) and as a result trip times tend to be shorter. Interestingly, we also observe that trip distances are longer, pointing to pedelecs being used for longer trips than normal bicycles.

Table 5: Use Differences between Pedelects and Bikes Considering Touring Trips

Variable	Pedelec Mean (N=788)	Bike Mean (N=607)	p-value
Total Distance (mile)	3.85	2.93	6.34E-10
Rate of Elevation Change (ft/ft)	0.00811	0.00906	1.27E-03
Trip Time (min)	43.7	46.0	1.87E-01
Total Speed (mph)	5.3	4.0	3.28E-26

Table 6: Use differences between Pedelects and Bicycles Considering O-D Trips

Variable	Pedelec Mean (N=1471)	Bike Mean (N=656)	p-value
Total Distance (mile)	2.43	1.92	1.50E-09
Rate of Elevation Change (ft/ft)	0.00736	0.00849	1.33E-04
Trip Time (min)	24.0	26.0	9.71E-02
Total Speed (mph)	7.1	5.3	4.22E-57

Table 7: Use differences between Pedelects and Bicycles Considering Commuting Trips

Variable	Pedelec Mean (N=85)	Bike Mean (N=24)	p-value
Total Distance (mile)	3.01	1.83	1.16E-03
Rate of Elevation Change (ft/ft)	0.00592	0.00469	6.37E-02
Trip Time (min)	31.0	24.2	1.40E-01
Total Speed (mph)	6.2	5.3	6.60E-02

However, the elevation traveled is lower for pedelecs than for bikes. This finding is counterintuitive since we were expecting pedelecs to be used to overcome higher elevations. In an attempt to understand in more depth the differences between pedelec and bicycle in terms of elevation, we defined three types of trips: touring (start and end points are the same), O-D trips (different start and end points) and commuting trips (trips between 6-10am during weekdays) and analyzed statistically significant differences between pedelec and bicycle trips using t-tests as described before. Table 5 through Table 7 show the results for this analysis. We can observe that commuting trips are the only ones that show higher elevations for pedelecs than for bikes, although the test is not statistically significant (p -value = 0.06) possibly due to the small number of samples in the test compared to the other types of trips (only 24 and 85 trips for pedelec and bicycles, respectively). However, this result reveals that RVA Bike Share users might be traversing higher elevations when using pedelecs for commuting, potentially pointing to convenience and speed. For commuting trips, the only significant difference between pedelec and bikes was the total distance; see Table 7.

For touring trips, total distance was longer (3.85 mi vs. 2.93 mi) and trip speeds higher (5.3 mph vs 4.0 mph) for pedelec bikes compared to bikes; however, there was no significant difference in travel time. While O-D trips had a much lower average distance, there was still a significant difference between trip distance for pedelecs (2.43 mi) versus bikes (1.92 mi). As with touring trips, the difference in travel time was insignificant.

Origin-Destination Trip Analysis

To analyze the frequency of different origin-destination trips, we grouped trips by their start and end stations and compared the number of trips across destination pairs for pedelecs and bicycles. Figure 14 and Figure 15 show the total number of trips for each pair of start and end stations, respectively. Consistent with the previous analysis, these plots show that the most frequent trips for both pedelecs and bicycles are trips starting/ending at Brown's Island/Canal Walk and at Monroe Park, pointing to exercise use since these are green areas. The second most popular trips are those that start and end at Broad and Harrison streets, a downtown Richmond location, pointing to secondary uses potentially related to shopping or recreational activities. It is also important to highlight that a chi-square test between the pedelec and the bicycle distributions revealed that both distributions were different (p -value=0).

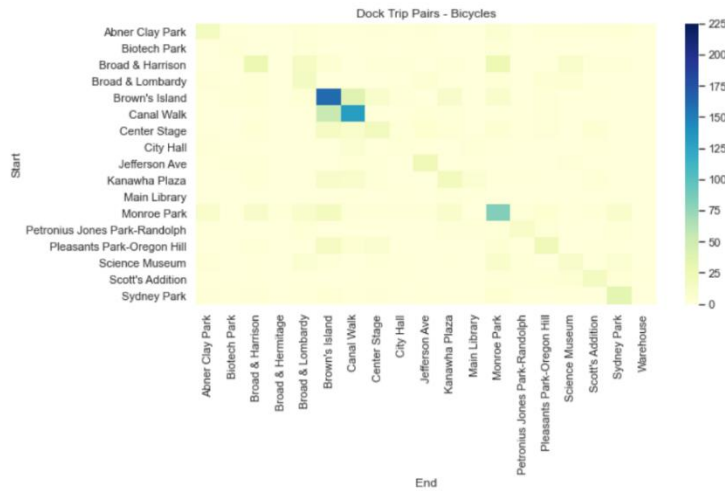


Figure 14: Start and End Trip Pairs for Bicycles

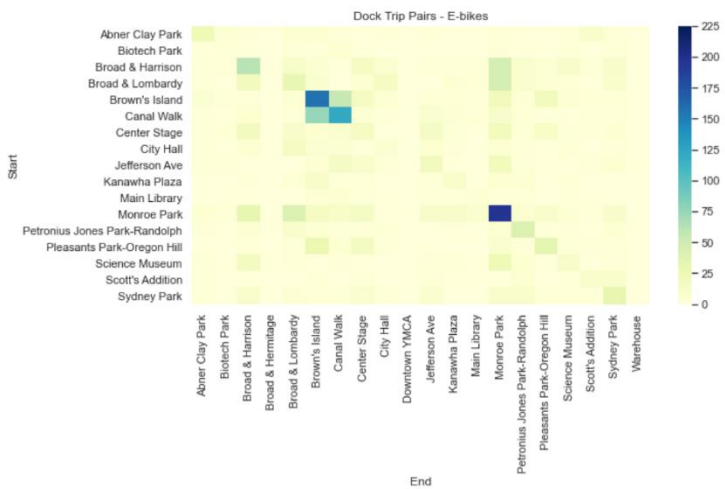


Figure 15: Start and End Trip Pairs for Pedelecs

In an attempt to better understand the types of locations visited, we also grouped trips by the type of origin and destination zoning code. We considered business, mixed use, residential and other uses. Figure 16 and Figure 17 show the volumes of trips for each zoning code pair for pedelecs and bicycles, respectively. We can observe that the plots show extremely similar trends with a large number of trips staying within either business or residential locations. We also observe considerable volumes of trips between mixed use and residential zoning codes, followed by business and residential. We posit that while the “other” trips might be representing exercise-type trips, the ones related to business and mixed use might reflect either shopping or other recreational activities, as discussed earlier.

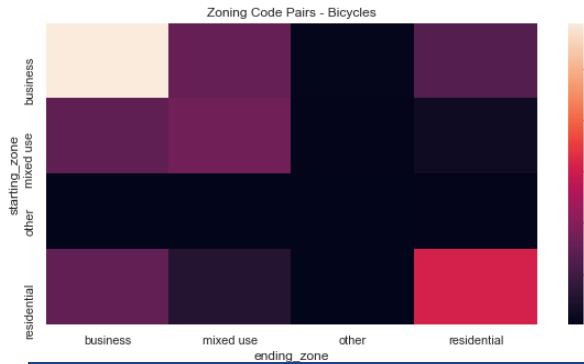


Figure 16: Start-End Zoning Code Pairs for Bikes

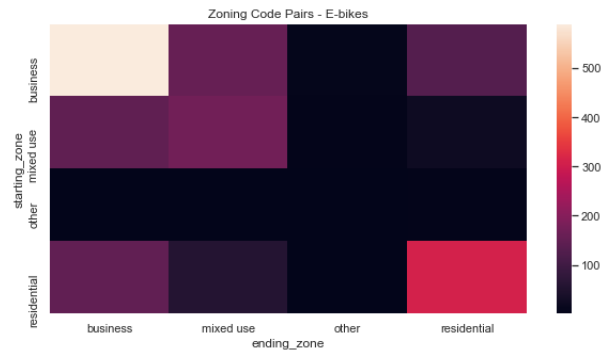


Figure 17: Start-End Zoning Code Pairs for Pedelecs

Roadway Use

To look at the routing differences between pedelecs and normal bicycles, we mapped the GPS trajectories of each trip using Mapbox’s Map Matching API as explained earlier; we break the snapped roads into segments and query each segment in Open Street Maps (OSM) to identify the type of road. Figure 19 and Figure 18 show the roadway segments used by pedelecs and bikes, respectively. The total number of trips that occurred on each segment was normalized by the number of trips on the segment with the maximum number of trips multiplied by 100. Thus, the road in pink has a frequency of 60%-100% of the road with the maximum number of trips. Pedelecs were used farther outside of the city than bikes. Additionally, pedelecs were frequently used in the downtown core where most RVA bike share stations are located. Both bikes and pedelecs were frequently used along the riverfront, Belle Isle, and the bike trail that runs south of downtown starting along the riverfront.

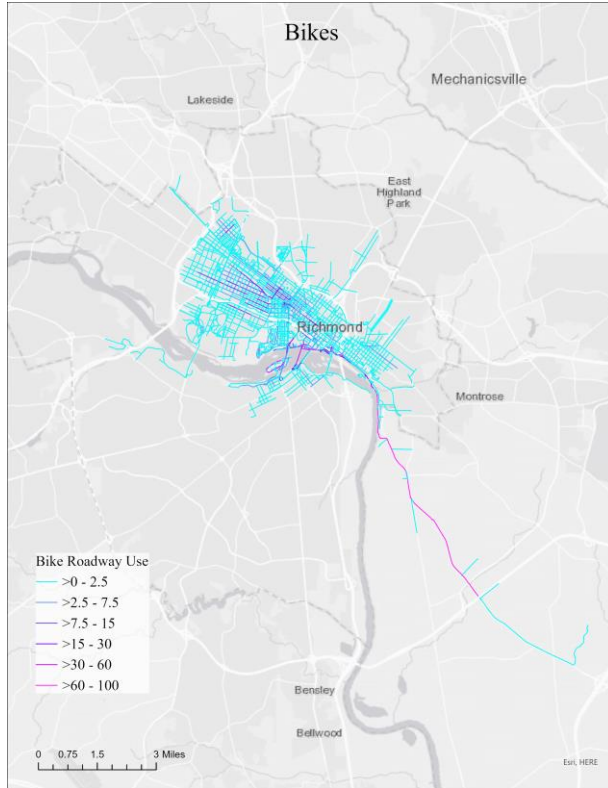


Figure 18: Normalized Roadway Use on Bikes

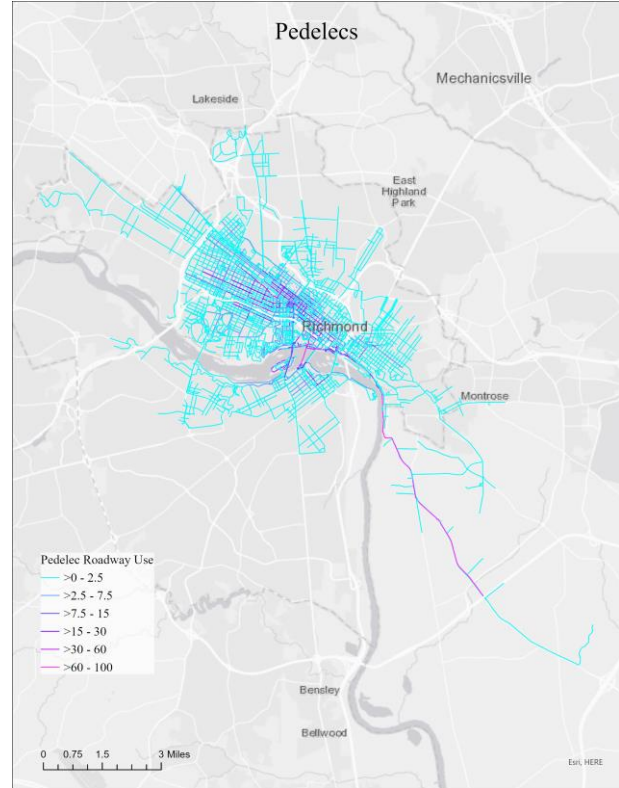


Figure 19: Normalized Roadway Use on Pedelecs

To analyze the types of streets traveled, we extracted from Open Street Maps the types of roads and we ran statistical tests (Welch t-tests) to compare the differences between pedelecs and normal bicycles with respect to their road usage.

Table 8 and Table 9 summarize our results for three different types of segments: major roads, minor roads, and roads with cycleways. For each segment, we report (i) the average number of miles traveled by pedelecs and bicycles, (ii) the average percentage of trip miles traveled by pedelecs and bicycles, the p-value that evaluates whether the reported differences are statistically significant ($p < 0.05$ shows that the difference in mean is significant). We can observe that pedelecs and bicycles have a higher average number of miles travelled on major roads than bicycles (0.84 mi. vs 1.28 mi.) and also a higher average percentage of the trip (45% of the trip vs. 36% for bicycles). On the other hand, pedelecs are associated with a lower average percentage of trips on minor roads (55% vs. 64%). Looking into roads with cycleways, Table 8 shows that pedelec users used rods with cycleways for a greater proportion of their trip than bike users.

Table 8: T-test for Mean Percentage of Trips by Pedelec or Bike on Select Roadway Types

Mean percentage	Major roads	Minor roads	Cycleways
Bike	36.00%	64.00%	28.21%
Pedelec	45.16%	54.84%	35.22%
p-value	7.52E-17	7.52E-17	4.26E-12

Table 9: T-test for Mean Mile per Trip by Pedelec or Bike on Select Roadway Types

Mean miles	Major roads	Minor roads	Cycleways
Bike	0.84	1.64	0.70
Pedelec	1.28	1.73	1.00
p-value	5.17E-19	1.73E-01	3.19E-09

RQ2. USER CHARACTERISTICS

For this analysis, membership types were grouped into five categories: (1) annual and annual founding membership, (2) monthly membership, (3) weekly membership, (4) day passes, and (5) one way and go passes. RVA Mural Bike Tour and Fall Offer Passes were excluded from the analysis since they are not regularly offered. In this analysis we focus on understanding bicycle type preference across memberships types.

For that purpose, we first grouped all the RVA users by membership type, and retrieved all the trips for each user in each group. Figure 20 represents the average proportion of trips on pedelecs for each membership type. The * represents the statistical significance of ANOVA tests that look into whether the differences in average fraction of trips are statistically significant across membership types. As Figure 20 shows, annual, monthly and weekly memberships are the ones with a higher fraction of pedelecs used, with average values between 0.65 and 0.85. Although these three groups have different averages, these values were not found to be statistically significantly different. On the other hand, one way/go and day passes have lower proportions of trips on pedelecs (0.6 and 0.5, respectively) and these average fraction values are statistically significantly different from all other membership types. This result suggests that members with longer-term passes might be more interested in using pedelecs, or that maybe those with short-term passes are not as aware of the existence of pedelecs, or not as interested in using them.

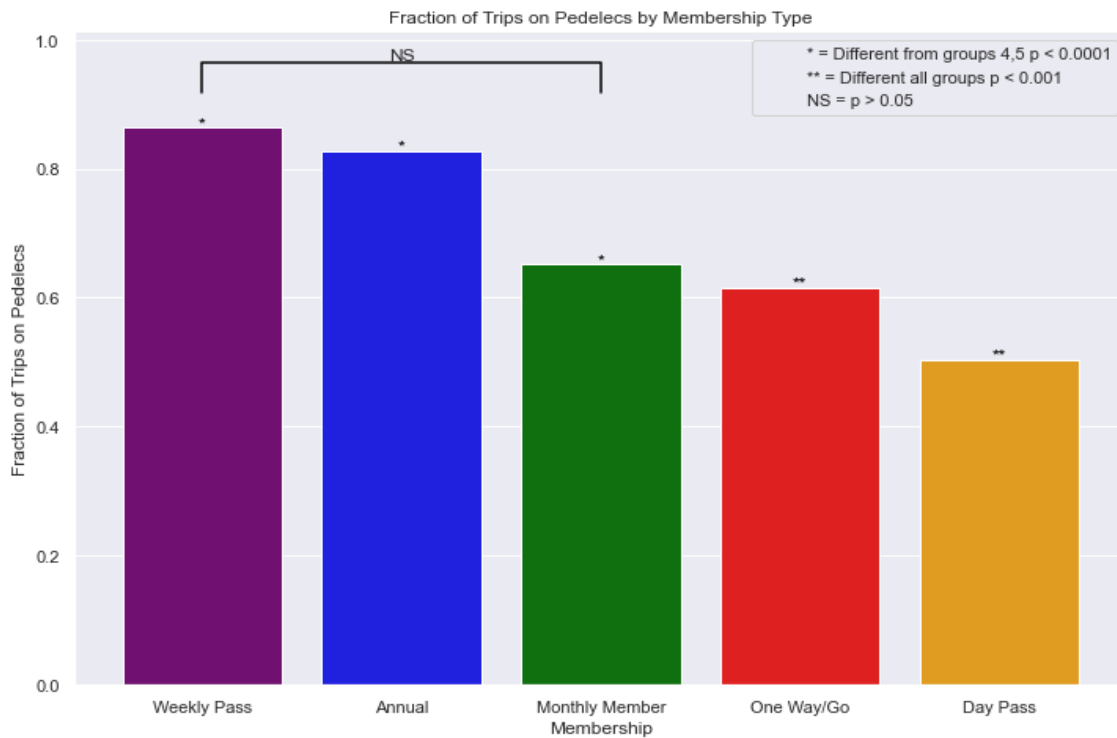


Figure 20: Statistical Analysis of Fraction of Trips on Pedelecs by Membership Type

To better understand potential reasons behind these findings, we analyzed other trip characteristics such as the proportion of weekend trips, average trip duration and average trip distance by membership category. The main hypothesis would be to test if longer-term memberships might be associated with certain types of trips that are more likely to be made on pedelecs than traditional bicycles. Figure 21 shows that longer-term memberships are associated with a lower proportion of weekend trips than shorter-term memberships, and that these differences are statistically significantly different for both monthly and annual passes. This might reflect that short-term passes are individuals using the bike share system for recreation and as a result they might prefer to use normal bicycles rather than pedelecs while longer-term membership riders might use the system more for weekly commuting or errands, favoring convenience and speed.

Figure 22 and Figure 23 show that trip duration and trip distance are longer for short-term passes, respectively. This result shows that recreational trips associated with short-term passes tend to be longer trips that cover longer distances. Putting it all together, we highlight that longer-term membership users favor pedelecs more than do those with shorter-term memberships, potentially due to the nature of the trips they make, with short-term membership holders favoring longer weekend trips that use normal bicycles more than pedelecs.

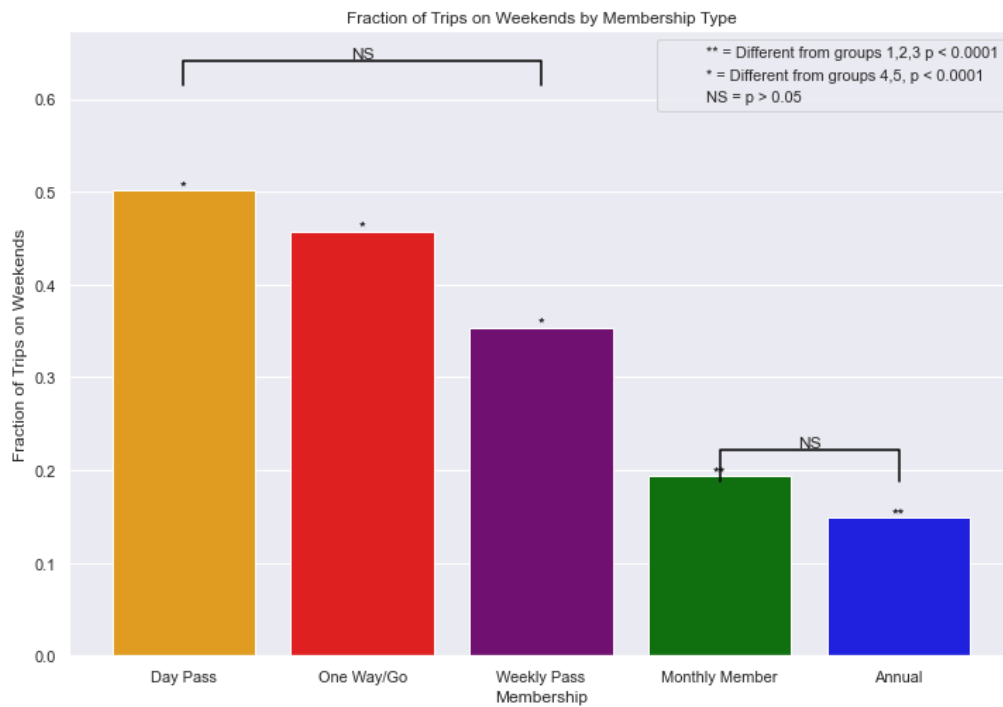


Figure 21: Statistical Analysis of Fraction of Weekend Trips by Membership Type

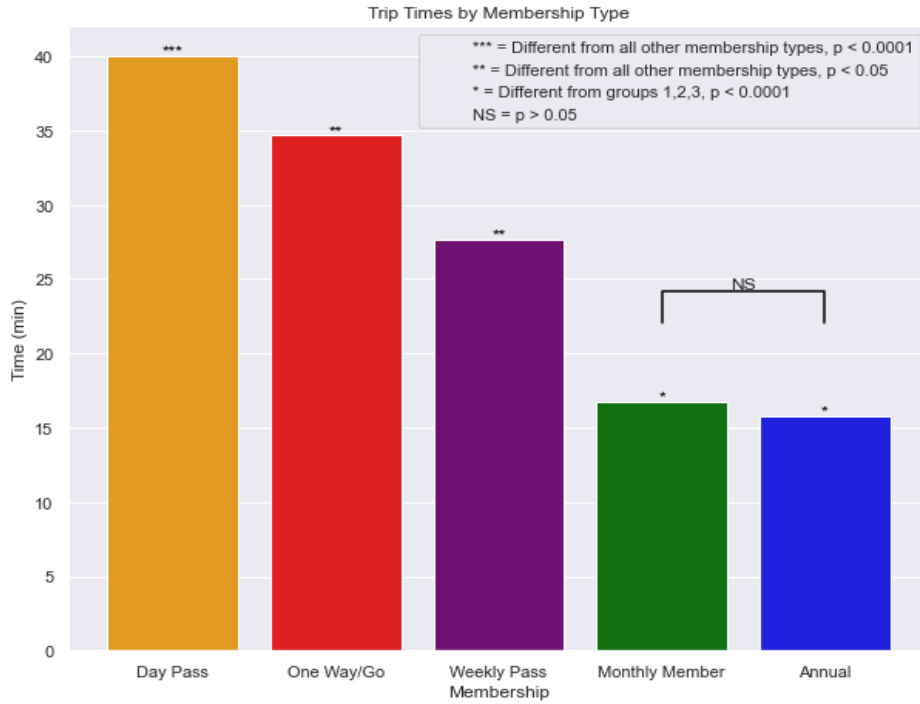


Figure 22: Statistical Analysis of Mean Trip Duration (in minutes) by Membership Type

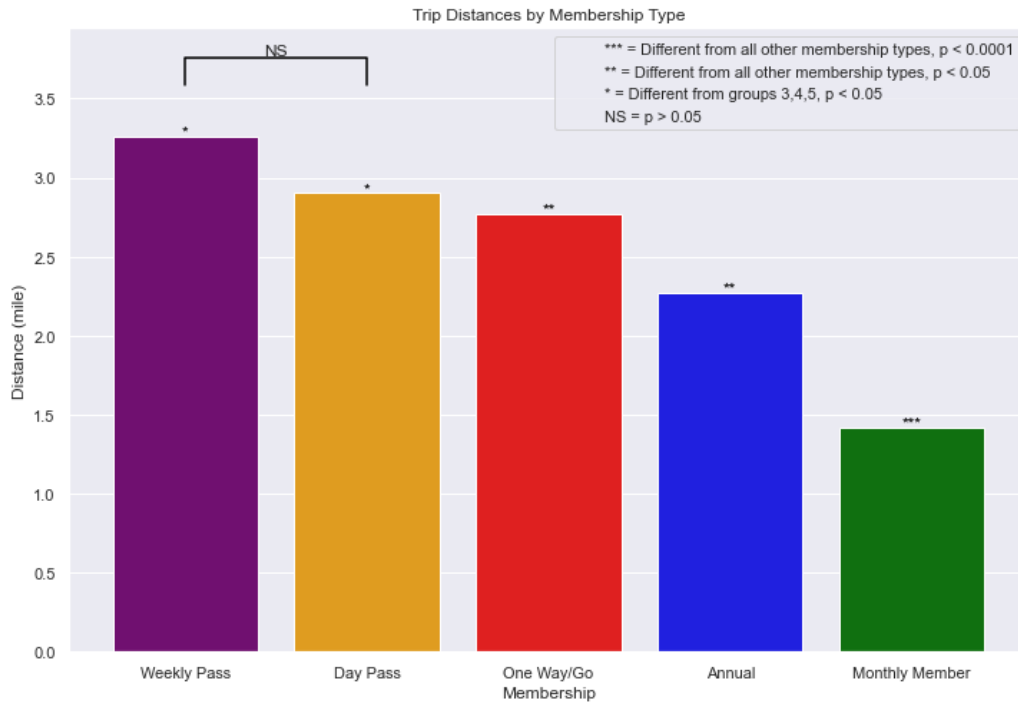


Figure 23: Statistical Analysis of Mean Trip Distance (in miles) by Membership Type

User Cluster Analysis

We conducted a user cluster analysis on the trip data. Specifically, for each user we considered the following variables: mean trip duration, mean trip distance, percentage of trips on the weekend, percentage of touring trips, mean starting trip hour and percentage of trips by pedelec. We used the K-means algorithm together with a measure of the inertia (within clusters sum of squares) to identify the final number of clusters [46]. Figure 24 shows the inertia for the various numbers of clusters considered in the analysis. We selected K=5 since that is where the “elbow” is located.

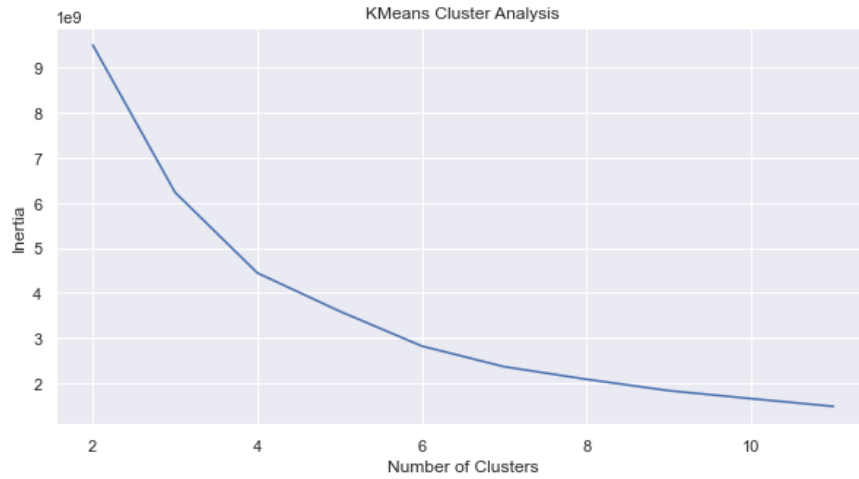


Figure 24: K-Means User Cluster Analysis Inertia Graph

Table 10: Summary of User Cluster Characteristics

User Group	Trip counts	Unique members	Average Trip Time (min)	Average Distance (mi)	Weekend Percentage	Touring Percentage	Average Starting Hour	Pedelec Percentage
0	694	288	42.3	4.2	44%	50%	12.8	71%
1	1135	512	34.5	2.6	47%	45%	13.2	60%
2	23	19	116.0	12.5	74%	87%	15.0	70%
3	197	137	68.7	6.7	47%	71%	13.4	68%
4	1363	469	15.6	1.2	36%	25%	13.7	64%
5	56	49	133.6	4.6	54%	70%	16.1	30%

Table 11: Membership Type Summary of User Clusters

User Group	One-way Go Pass	Day Pass	Weekly Pass	Monthly	Annual
0	60%	12%	14%	0%	14%
1	71%	25%	1%	2%	1%
2	70%	30%	0%	0%	0%
3	76%	22%	2%	0%	0%
4	57%	13%	3%	9%	18%
5	61%	37%	2%	0%	0%

Table 4 shows a summary of the main characteristics for each of the groups identified. *Trip counts* is the number of trips in the cluster; *unique members* represent the unique users in this group; *average total trip time* is the average trip time in seconds; *average total trip distance* is the average distance in meters; *weekend percentage* is the percentage of trips in the cluster that are made during weekends; *round trip percentage* is the percentage of trips that are round trip; *average starting hour* is the average starting hour of the trip during the day; *pedelec percentage trip* is the percentage of trips in this group that are pedelec trips; and *membership type* represents the percentage of trips associated with each membership type in that cluster.

Annual members generally only fell into user groups 0 and 4; see Table 11. User group 0 was characterized by longer trips (42.3 min vs 15.6 min) that were more likely to start and end at the same station (touring trips). As shown in Figure 25a and Figure 25e, more roadways were used in user group 0 versus group 4. Additionally, user group 0 frequented Belle Isle and the bike trail that runs south along the riverfront. User group 4 were annual members who largely took O-D trips in central Richmond.

User groups 2 and 5 are characterized by trips with a long duration (116 min and 134 min, respectively). User group 2 had an average trip length of 12.5 miles whereas group 5 only 4.6 miles. Group 5 had the lowest pedelec use (30%) out of any other group; about 70% of group 2 trips were by pedelec. Group 2 had the largest percent of touring trips (87%). Both categories only contained riders who were short-term or paid by the ride. As shown in **Error! Reference source not found.c**, user group 2 trips were the farthest outside of the city compared to the other groups, with the most frequently used roads containing bicycle facilities. Group 5 trips were concentrated along the recreational areas (Belle Isle and Riverfront Trails). Group 5 had the least proportion of trips in central Richmond (Figure 25f).

Like group 2, group 3 has a high percentage of touring trips (71%); however fewer trips occur on the weekend (47% vs. 74%). Both group 2 and 3 have a similar membership makeup. Reflective of the trips taking place during the weekday, group 2 trips are shorter in length (6.7 mi vs. 12.5 mi) and duration (69 min vs. 116 min). Compared to group 2, user group 3 (Figure 25d) trips were more centralized; however, the most frequently used roads were to the recreational areas of Belle Isle and along the riverfront trail. While the roadway use of group 3 (Figure 25d) was similar to that of group 0, trips were shorter.

Group 1 trips were short (2.6 mi). However, when comparing group 1 to group 4, despite similar travel distances (2.6 mi vs 1.2 mi), the average travel time in group 1 was considerably longer (35 min vs. 16 min). Like group 4, group 1 trips frequented the roads in central Richmond where most of the bike share stations are located; see Figure 25a and Figure 25e. Unlike group 4, group 1 users also traveled along the recreational roadways.

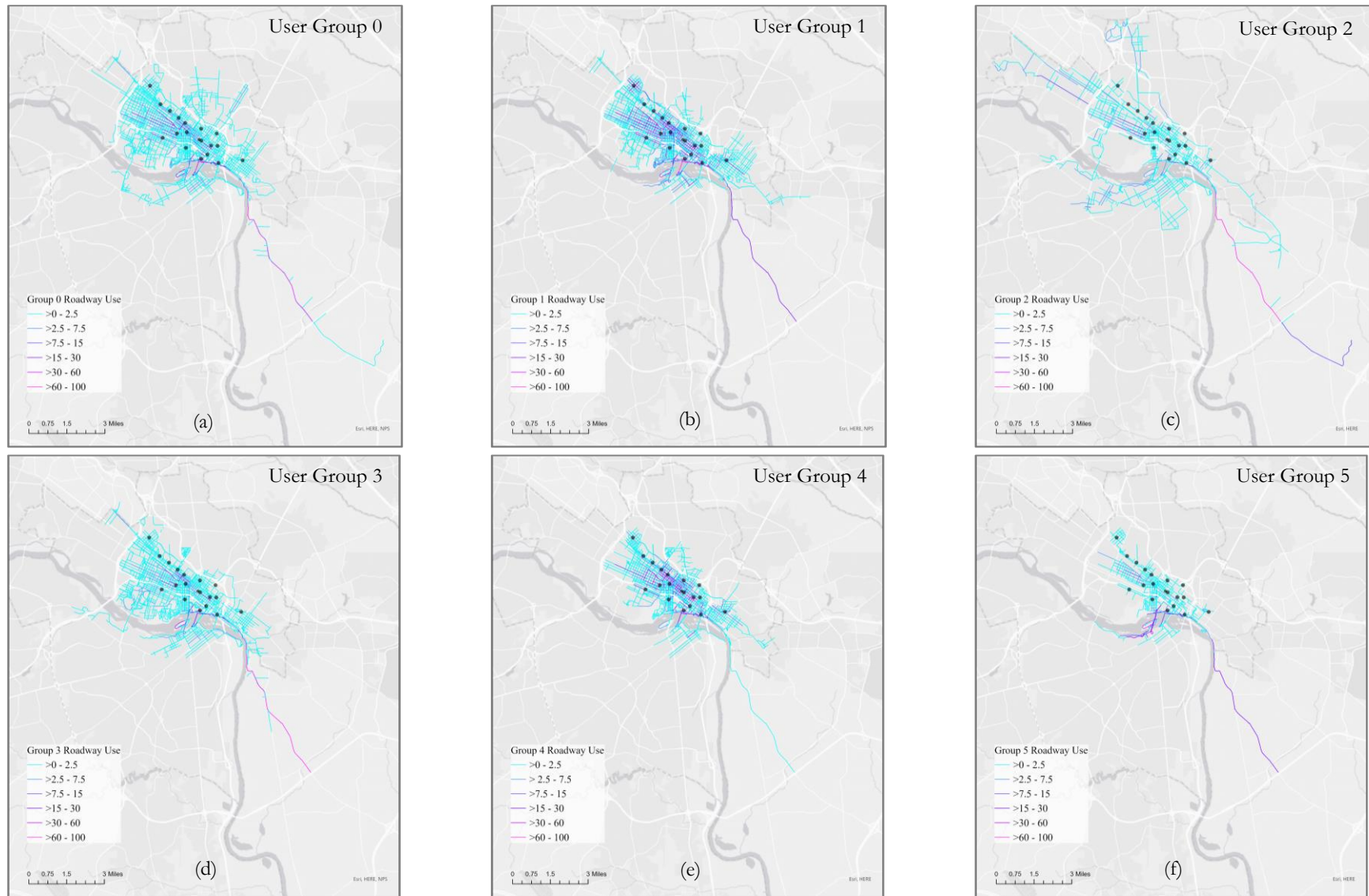


Figure 25: Normalized Roadway Use for User Clusters

CONCLUSIONS

This work has presented a comprehensive analysis of the similarities and differences between pedelec and normal bicycle use in Richmond, Virginia, and an evaluation of how membership type and other user characteristics might influence bike share use. Our results have shown that pedelecs are generally associated with longer trip distances, shorter trips times, higher speeds and lower elevations. These results were similar across types of trips: touring, O-D and commuting, with the exception of commuting trips where elevations were higher, possibly pointing to convenience and speed when going to work. The study area is relatively flat; thus, future work should consider the impact of elevation in an area with hillier terrain.

Pedelecs were also found to be associated with higher average numbers of trips on major roads than bikes, and with lower volumes of trips on minor roads than bikes. Origin-destination analysis on pairs of stations has shown two popular pairs mostly associated with recreational activities both for pedelec and normal bicycles. In terms of memberships, longer-term memberships (annual, monthly) were found to be associated with significantly higher use of pedelecs than shorter-term memberships, potentially pointing to a lack of knowledge on the part of individuals who use the system with less frequency, or to a preference for normal bicycles. Finally, the user cluster analysis identified six diverse types of behaviors that varied by geographical region (e.g. central Richmond vs. recreational areas), as well as by trip distance, trip duration, and bike type.

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