A comparison of electric and non-electric bike sharing in Montréal, Canada

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Abstract. A growing number of cities have added electric-assist pedal bicycles to their existing public bike sharing systems. While reception of these e-bikes has been largely positive, still little is known about how their usage differs from traditional non-electric bicycles. In this paper I examine and identify the spatial and temporal differences in usage behavior between electric and non-electric bikes in a public bike sharing system. Using data from Montréal's BIXI operator, I find that e-bikes tend to be used for slightly longer trips, on weekends and during peak evening commute, and show greater spatial dispersion across docking stations than non-electric bicycles.

Keywords: e-bike, bike sharing, bicycle, electric bike, spatial analysis

1 Introduction

Electric-assist pedal bicycles (e-bikes) are dramatically changing the urban mobility ecosystem. Over the past few years, e-bikes have become a reliable means for both commuting and recreational travel. In 2021, the global e-bike market was valued at US$17.6 billion and is projected to reach almost US$41 billion by 2030 [23]. Many large, municipally-funded bike sharing programs have taken notice and begun to introduce e-bikes into their fleets. While the majority of public bike sharing systems still rely on traditional non-electric bicycles, the influx of commercial micromobility operators into cities (e.g., Lime e-scooters) has encouraged government-funded cycling programs to offer new modes of transportation.

The introduction of these e-bikes into major urban bike sharing systems prompts a number of questions that are of interest to both city officials and the public. How are these new vehicles being used? How does their usage differ from traditional non-electric bicycles? While a substantial body of literature has researched traditional docking station-based bike sharing platforms [10], little work has explored the difference in activity behavior between non-electric and electric-assist bikes in the same system. Still fewer researchers have examined this from a spatiotemporal perspective with the goal of understanding how these services differ in *where* and *when* they are used. In this short paper I will address this through the following two research questions (RQ).

> *Is there a significant difference in the temporal (`RQ1`) and spatial (`RQ2`) activity patterns of e-bikes and traditional bicycles in major, docking station-based, bike sharing systems?*

To address this question I analyzed data from Montréal's BIXI program. Launched in 2009, BIXI (a hybrid of BIke and taXI) is North America's longest running large-scale bike sharing service [22]. In the last year BIXI registered 437,140 unique users and reported more than nine million trips [5]. The service uses docking stations where a user can unlock a vehicle at one station and ride it to another. When the system was first introduced it consisted of only traditional bicycles, but in early 2019 BIXI introduced a fleet of blue e-bikes into their system. These new e-bikes were greeted with skeptical optimize by BIXI riders [7] but are actively in use by visitors and commuters today [6]. In fact, BIXI has increased the number of electric-assist vehicles year after year since their introduction [8]. In this paper, I will differentiate the two vehicle types by referring to electric-assist pedal bicycles as *e-bikes* and traditional non electric-assist bicycles as simply *bicycles*.

2 Related work

Existing research on bike sharing systems has largely explored the impact that the introduction of new systems has on urban populations. For instance, Fuller et al. [11] found that the introduction of a bike sharing system (BIXI in this case) led to an increase in active transportation among people living in areas where bikes were made available. Other research has demonstrated that the introduction of bike sharing systems complement existing modes of public transportation [13, 16, 26] but do not necessarily replace car trips [3]. There are notable differences and motivations between e-bike users and bicycle users with some researchers finding that e-bike users were more likely to take public transit [1, 4] should e-bikes not be available. Contradictory research found that usage in e-bikes and bicycles appears to be the same with slight variations due to distance and route gradient [25]. The demographics and factors leading to e-bike usage vary by region through with price, income, and availability playing a important roles [21, 9].

Very little research has compared different vehicle types on the same public bike sharing system. In one such study, Reck et al. [24] compared docked e-bikes and bicycle usage in Zürich, Switzerland finding that both services exhibited similar temporal patterns, peaking during heavy commuting hours. Additional work has compared public bike sharing systems with other micromobility systems. For example, research by McKenzie [18] compared docking station-based bike sharing systems with new dockless electric scooters in Washington DC finding that there were notable spatial and temporal differences in usage. Further work investigated various factors that could explain the differences between public bike sharing system use and new mobility services including gas prices [28], weather [12], and holidays [14].

From analysis perspective, a growing body of work has investigated spatial and temporal usage patterns of bike sharing systems. Bao et al. [2] used spatial regression models to predict mobility patterns while others have used a variety of machine learning methods to make spatial predictions [19, 27]. A large body of work has focused on optimizing redistribution of vehicles [15] with many papers discussing the engineering tasks necessary for improving the efficiency of vehicles themselves. Despite the amount of existing literature on bike sharing, a comparison of e-bike and bicycle activity behavior on a single public bike sharing system remains as a research gap.

3 Methodology

For this work, I restricted my analysis to a 138 day period from June 18th through November 3rd, 2021. These dates are based on when I first gained access to the BIXI e-bike application programming interface (API) and the final month of operation for BIXI's 2021 season.

3.1 Data

Yearly trip data are published through BIXI's open data portal [5]. In these data, each trip consists of an origin station, destination station, start timestamp, and end timestamp. Geographic coordinates and station names are associated with each station in the dataset. Notably, the data do not include a vehicle identifier, user identifier, or type of vehicle. Restricted to the 138 day analysis window, a total of 4,001,081 trips were reported.

Since BIXI does not publish the vehicle type in their public trip data set, one is unable to identify which trips were completed using a bicycle and which used an e-bike. To accomplish this task, I access data reported on the *available vehicles map* published on the BIXI website (https://secure.bixi.com/map). This interactive map reports real-time availability of vehicles and differentiates between e-bikes and bicycles. Data on the map is fed through an API[1] that returns the vehicle and station identifiers for all available vehicles with every request. In requesting the set of available vehicles every minute over the course of 138 day I was able to reconstruct trips. This was accomplished by identifying when and where a vehicle disappeared from the available vehicles data set and then reappeared in the data set. This approach followed the trip reconstruction process outlined by McKenzie [17]. Using this method, I identified 898,566 e-bike trips using a total of 1,721 unique vehicles.

[1] https://layer.bicyclesharing.net/map/v1/mtl/map-inventory

Next, I compared the set of e-bike trips with those accessed through BIXI's open data portal, with the goal of identifying which trips used e-bikes and which used bicycles. This matching process involved identifying trips with the same origin and destination stations, as well as the same start and end timestamps. A buffer of five minutes was added to the start and end times to account for data collection frequency offsets and report delays from the BIXI platform itself. After matching, a total of 687,302 unique e-bike trips were identified. The difference between the original number of e-bike trips, and the matched e-bike trips can be largely explained through redistribution. Throughout the day BIXI redistributes their vehicles via truck to balance their fleet and ensure users always have access to vehicles.

3.2 Temporal analysis

After data collection and cleaning, we calculated the median trip duration and distance for each of the vehicle types as well as the average number of trips per day. To address `RQ1` I ran a difference in means *t-test* for trip duration and trip distance. Trip distance in this case was reported as the Euclidean distance between two stations as I do not have access to route distance.

Next, I calculated the aggregate temporal usage pattern for each of the vehicle types by binning trips into hours of the week. For both data sets combined, the number of trips for each hour of the week is shown in Figure 1. These patterns reflect typical usage behavior with increased trip counts during weekday commuting periods and less pronounced behavior during the weekends. I then split these temporal patterns by vehicle type with the objective of identifying differences in temporal behavior throughout the week.

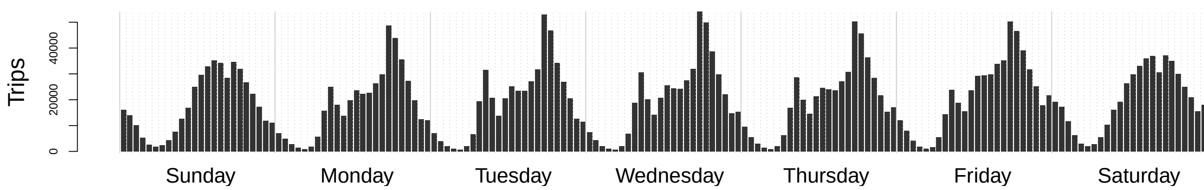

Fig. 1: Trip count by hour of the week

There is an order of magnitude difference between the trips taken using e-bikes and those taken using traditional bikes. This makes it impossible to compare the two vehicle types at the level of raw trip counts. Instead, I assessed the *relative* difference in popularity of each service at different times of day. For instance one service might show a greater percentage of its overall usage on the weekend than weekdays. To accomplish this I normalized each of the hourly trip counts by the maximum hourly trip count for the week. This resulted in a temporal *popularity* pattern where all values were bounded between zero and one. This was done for both temporal patterns independently. I then subtracted each hourly popularity value in the e-bike temporal pattern from it's corresponding hourly value in the bicycle temporal pattern with the goal of identifying which vehicle type was relatively more popular, at different times of the week.

3.3 Spatial analysis

To address `RQ2` I explored the different spatial patterns resulting from users of e-bikes with those of bicycles. E-bike trips and bicycle trips were aggregated by station of trip origin independently. If I were to simply look at which station had the highest number of trip origins, bicycles would clearly dominate given the much higher number of trips. Similar to the temporal analysis, these trip counts were normalized so that all station values were bounded between zero and one. This allowed us to identify differences in relative spatial popularity. In other words I could identify which vehicle type had a higher percentage of their overall trips at which stations. This speaks to the spatial behavior of users. Station popularity values were then subtracted from one another to identify which stations were *relatively* dominant. A map of the stations was generated for visual analysis of the clustering. To report on the statistical differences between vehicle trips, I conducted a *global Moran's I* analysis [20] to identify the degree of spatial auto-correlation in each of the vehicle data sets. My goal was to determine if one vehicle type was more spatially clustered than the other.

4 Results

4.1 Temporal behavior

While there is a substantial difference between the number of trips, the median trip duration and distance is relatively small with e-bike trips being longer and farther than bicycle trips on average (Table 1). The results of the difference in means *t-test* indicates that for both variables, *Distance* and *Duration*, the means were significantly ($p < 0.01$) different.

Table 1: Descriptive statistics for BIXI trips, split by vehicle type. Note that distance is measured as Euclidean distance between the origin and destination stations.

	Electric bike	**Traditional bicycle**
Trips	687,302	3,313,779
Median Trips per day	5,293	25,127
Median Duration (seconds)	664	622
Median Distance (meters)	1,997	1,417

Analysis of temporal patterns over the hours of the week demonstrated that there are small, but notable differences between the two vehicle types. While bicycle trips remained high throughout the week, e-bike dominance was more sporadic. Figure 2 shows normalized e-bike trips subtracted from normalized bicycle trips. From this perspective, a greater percentage of e-bike trips took place on weekend afternoons and during evening rush hour than bicycle trips. In contrast, bicycle usage showed more even distribution over the hours of the week.

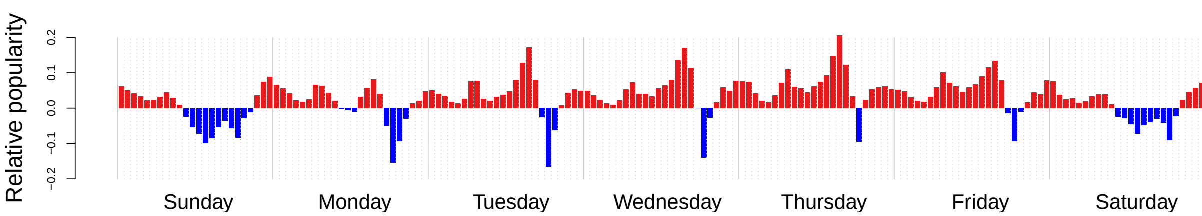

Fig. 2: Relative popularity of vehicles aggregated to hours of the week. Normalized e-bike trips are subtracted from normalized bicycle trips. Blue negative values represent e-bikes. Red positive values represent bicycles.

4.2 Spatial behavior

The results of the station-based spatial analysis are shown in Figure 3. Station-normalized e-bike trips were subtracted from bicycle trips. Negative values are shown in shades of blue. These blue stations indicate that a greater percentage of all e-bike trips originated from these stations than the percentage of all bicycle trips. Positive values are shown in red and indicate stations where bicycle were the *relative* dominant vehicle in use.

In visually analyzing this map one sees clear spatial clustering. A greater percentage of bicycle trips originate at stations in the downtown core, as well as the *Plateau* and *St. Henri* neighborhoods. E-bike usage appears to be more widely dispersed with a larger percentage of trip origins being distributed in regions outside of the downtown core. The global Moran's I analysis of both data sets confirmed the visual assessment and found that there is a higher degree of spatial auto-correlation in the bicycle trip origins ($I = 0.384$) than the e-bike trip origins ($I = 0.344$), both with an expected value of -0.0013 using Euclidean inverse distance weighting.

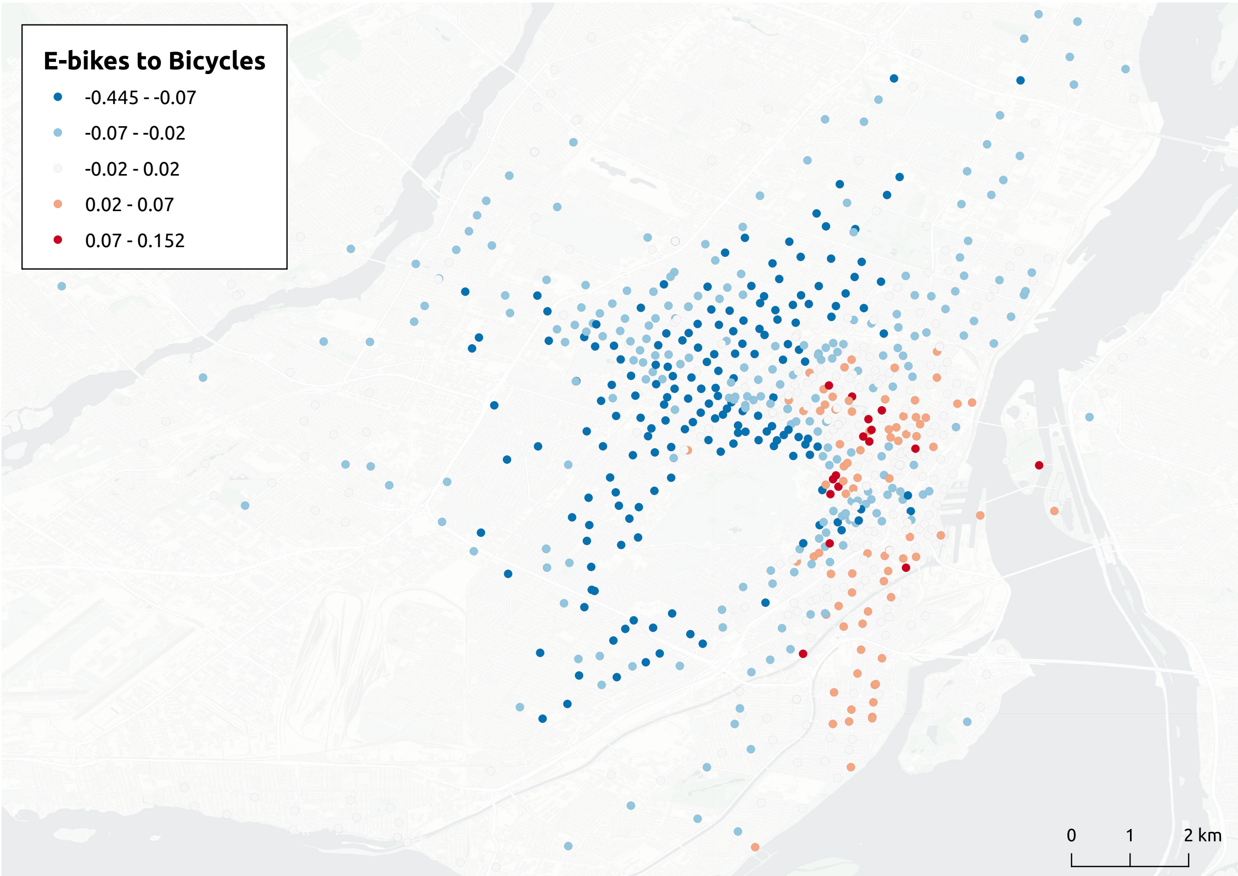

Fig. 3: BIXI stations styled by relative dominance of vehicle type. E-bike and bicycle trips were aggregated by station. Normalized e-bike trips were then subtracted from normalized bicycle trips.

5 Discussion

In this short paper I present a comparative analysis of two vehicle types in a large public bike sharing system, namely e-bikes and traditional bicycles. The analyses contrasts the spatial distribution of trips as well as temporal properties. Through these analyses I discovered that e-bike trips tend to be slightly longer in duration and distance than bicycle trips. Given this increase in distrance and duration, it follows that a greater percentage of e-bike trips would originate at stations outside of the downtown core than bicycle trips. The spatial analysis confirms this and suggests that bicycle trip origins are more clustered than their electric counterparts.

While every effort was made to accurately analyze the data and report the finds, there were limitations. The process through which e-bike trips were matched to the data from BIXI's open data portal is not exact. Due to data collection frequency and lack of transparency in the temporal precision of reporting from BIXI, exact matches were difficult to ascertain. The temporal buffering technique was useful in matching trips between data sets, but it is likely that a small number of trips were mislabelled. Given the volume of trips, it is unlikely that any mislabelled trips would have altered the overall findings.

Finally, this short paper presents my preliminary work on subject. Further analysis will mix the temporal and spatial dimensions in order to identify spatial variation in trips depending on time of day. BIXI, like many large bike sharing systems offers different membership options. Analysis by membership type may be of interest to the operator and city officials. Finally, we know that bike sharing usage behavior is also influenced to socio-economic and demographic factors. In future work, I will explore how these factors effect vehicle choice and trip dynamics.

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