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To cite this article: Wissam Kontar *et al* 2022 *Environ. Res.: Infrastruct. Sustain.* **2** 035006

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ENVIRONMENTAL RESEARCH
INFRASTRUCTURE AND SUSTAINABILITY

OPEN ACCESS

RECEIVED
9 March 2022

REVISED
10 June 2022

ACCEPTED FOR PUBLICATION
28 June 2022

PUBLISHED
5 August 2022

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PAPER

Electric bicycles sharing: opportunities and environmental impacts

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Keywords: electric bicycles, micro-mobility, life cycle assessment, environmental impacts, transportation

Supplementary material for this article is available online

Abstract

Electric bicycles (E-bikes) are an emerging transportation technology with the potential to replace other available modes. In this work, we investigate the ability of an E-bike sharing program to compete with different modes of transportation and the resulting use-phase environmental impacts. A survey study on users of an E-bike program in Madison, Wisconsin was conducted to reveal modal shifts before and after access to the program's membership. An environmental investigation based on well-to-wheel life cycle analysis, coupled with mode choice modeling reveals the users of this technology, the underlying modal shifts triggered by its usage, and the cascading environmental implications. The analysis reveals E-bike's ability in attracting users, which translates into beneficial environmental impacts across five studied categories: energy consumption, greenhouse gas emission, particulate matter, sulfate and nitrate emissions. We further explore the implications of trip distance on the ability of E-bikes to compete with other modes of transportation, and the resultant environmental impacts. Finally, the electricity generation scheme is analyzed to showcase the dependency between environmental benefits of E-bike and the energy infrastructure it is operating under.

1. Introduction

The search for alternative modes of transportation has seen a spike in interest with the growing concern about various environmental impacts of the transportation system. It is estimated that 28% of the greenhouse gas emissions (GHG) in the United States (U.S.) comes from the transportation sector [1]. This significant contribution from transport emissions presents an urgent need to reduce overall GHG emissions in the U.S. by adopting environmentally-friendly modes of transportation. Indeed, over the past decade travelers have witnessed a growing number of such transportation modes, with electric options surging the market (electric vehicles, hybrid vehicles, e-scooters, electric bicycle (E-bike), etc) [2–7]. With the presence of different modes of transportation, comes an intricate web of choices that can alter transportation demand and in turn have potential environmental implications. The change in travel demand, more specifically the change in mode choices, is important in reforming the environmental blueprint of the transportation systems. For instance, shifting travelers from carbon-intensive modes (e.g., vehicles) into much less intensive modes (bicycles, or E-bike) can have drastic impacts. Such shift has already been set in action with increasing popularity of biking as an alternative mode of transportation and has been brought to life through the usage of bike sharing programs [8–11]. In fact, between 2018 and 2019, the U.S. has witnessed a 60% increase in shared micro-mobility trips (shared bikes and scooters) [12]. Specifically, the E-bike has been a major influence to bike share popularity as it requires less effort than its predecessor; the bicycle [13–15]. Accordingly, this work presents an analysis into the nature of use-phase environmental impacts resulting from the adoption of E-bike and its ability in replacing other modes of transportation (e.g., car, bus, conventional bicycle, and walking).

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Unlike traditional bicycles, E-bikes are equipped with an integrated battery that augments the pedal power, boosting the rider's cycling power and giving them the sensation of cycling with a tail wind [16]. E-bikes are inherently faster, more navigable in hilly areas and are more accessible to those who might be averse to cycling [13, 17, 18]. These benefits make the E-bike more competitive with other current travel modes such as conventional bike, driving, and transit. Note that various kinds of E-bikes exist, including fully motorized and pedal-assisted E-bikes. In this paper, we consider the latter: the E-bike that is assisted by an electric motor but requires some level of pedaling.

Literature has recently begun exploring the potential benefits of E-bike and the associated behavior of their users. The vast majority of experimental studies on E-bike are done in Europe and China, where travelers are well-versed with bicycle commuting [18, 19, 19–23]. However, more insights on the impact of E-bikes, particularly E-bike sharing programs, in the U.S. should be gathered. These insights would complement the rising interest of many metropolitan areas in the U.S. to accommodate more environmentally friendly modes of transportation [24]. Additionally, most available studies focus on personal E-bike (i.e., owned E-bike) and not E-bike sharing programs which have different travel behaviors. For instance, Cairns *et al* [25] reviews the travel behavior of electrically assisted bikes, and performs and experimental study in Brighton, United Kingdom, collecting usage pattern data of 80 employees loaned an E-bike. Their analysis shows the overall attractiveness of E-bike and their ability to substitute car use. Brand *et al* [26], shows through a longitudinal panel study across different European cities the benefits of active mobility in decreasing transportation emissions. Gorenflo *et al* [27] collected sensor data from 30 E-bikes given to members of the University of Waterloo, Canada. Their experiment, which lasted nearly three years, showed that the primary usage of E-bike by the participants was commuting, with most trips being less than 20 min. Interestingly, they note that their participants rated conventional bicycles higher than E-bike, which they attribute to the lack of familiarity of the Canadian population to E-bikes and their potential. Fyhri and Fearnley [28] performed an E-bike usage study based on 66 participants in Norway. The study concluded that E-bikes are practical for everyday travel. The study also noted that a greater usage of E-bikes was found among female cyclists.

While the above studies present some insights into E-bike usage patterns, their environmental impacts are less known, and insights on E-bike sharing programs are yet to be gained, especially in the U.S.. Notably, some recent insights exist on shared E-bike travel behavior. For instance, Campbell *et al* [29] uses stated preference survey in Beijing to reveal that demographics play significant role on E-bike sharing demand and that E-bike sharing is an attractive bus replacement mode. Guidon *et al* [30] uses data from an E-bike sharing system in Zurich, Switzerland to reveal that distance range of such mode overlaps with public transportation and taxi services. He *et al* [31] studies the demand of an electric bike share system in Park city. The paper shows that weather factors, wind speed, proximity to public and recreational centers impact the demand on these systems. Recently, Fukushige *et al* [32] studied dock-less E-bike sharing in Sacramento, California. Interestingly, their analysis reveals strategic deployment of bike sharing program in ways that allow substitution of car trips by E-bikes. These strategic deployment techniques consider influencing factors such as income, availability of private cars, gender, and proximity to commercial or non-commercial locations. Another study on North America's first E-bike sharing system by Langford *et al* [33] reveals some factors influencing the usage of E-bikes. Notably, the study concludes that the bike sharing system (E-bikes and conventional bikes) was successful in attracting users towards biking.

Other, albeit few studies have looked at quantifying environmental impacts of E-bikes, yet these broadly focused on general patterns and technological aspects, with little connection to usage pattern in competing scenarios with multiple available modes. A noticeable study by Elliot *et al* [34], quantifies the environmental impacts of people switching from other modes of transportation towards E-bike in Wellington, New Zealand. The paper concludes with positive environmental impacts of E-bike. Another recent study by McQueen *et al* [35] shows that personal E-bikes are capable of reducing an average of 225 kg CO_2 per year, due to their ability of replacing car trips.

Clearly, E-bike has a promising potential as an alternative mode of transportation, and their adoption can be accompanied with unique usage patterns and travel behavior. However, a critical piece of the story is yet to be explored: the link between E-bike share usage and its respective environmental impacts on the transportation system in presence of other competing modes of transportation. Essentially, it is critical to understand the E-bike's ability to replace trips currently done by other modes of transportation and what is the resultant environmental impacts of this modal shift. In this paper, we adopt a comprehensive empirical approach into quantifying the environmental impacts of E-bike and their potential in replacing other modes of transportation. Towards this end, a survey is used to gather usage patterns from users of a popular E-bike sharing program, BCycle, in the city of Madison, Wisconsin. Based on the survey data, a mode choice model is developed for E-bike usage pattern in conjunction with various available modes of transportation in the city: personal vehicle, bus, conventional bike, ride-hail and walking. This allows for a direct quantification of environmental

impacts of E-bike usage, by linking modal shifts with the use-phase environmental analysis known as well-to-wheel (WTW) life cycle analysis (LCA). This study considers four different environmental categories: energy consumption, greenhouse gas emissions, particulate matter emissions, and pollutants emissions (sulfates and nitrates). The analysis reveals that E-bike sharing has potential in competing with available modes. E-bikes are able to decrease use-phase environmental impacts of transportation systems, however this is dependent on different factors. First, E-bike sharing programs are most effective in competing for ridership at short distance trips. When they compete with modes as conventional bike or walking they add further use-phase emissions, as they are dependent on electricity. However, they have shown potential in replacing some carbon-intensive modes (vehicles, buses) which is shown to reduce the overall use-phase environmental emissions. Second, the energy infrastructure, specifically electricity distribution mix can play a role in the extent of environmental benefits seen from E-bikes.

The remainder of the paper is organized as follows: section 2 provides methods for survey design, mode choice model development and environmental analysis. Section 3, provides results and discussion, and finally section 4 concludes with study limitations, future work and final remarks.

2. Methods and modeling

2.1. Survey design & data collection

A web-based survey was distributed to members of BCycle in Madison, Wisconsin, a medium sized city. BCycle is a bike sharing system with fully electric fleet (peddle assisted E-bike). This bike sharing system allows its members to check out E-bike at various dock stations and return them to any stations around the city to serve their specific travel needs. A total of 667 responses were received, of which 450 were used as a final dataset after data filtering.

The survey consisted of three main parts. The first part was designed to gather socio-demographic information of the participants. In the second part, participants were asked about general travel behavior and their attitudes towards E-bike. The third part was specifically designed to gather data on respondents' mode choice before and after owning a BCycle membership. Specifically, participants were asked to provide travel attributes (distance and time) of different trip types and state their mode of transportation used. The survey considers six different mode choices: personal vehicles, bus (the public transport system in Madison), ride-hail, conventional bike, E-bike, and walking. Consequently, the collected data will allow us to quantify the modal shifts triggered by E-bikes as well as inform a mode choice model to reveal the characteristics of E-bike users. Readers are referred to the supplementary information (https://stacks.iop.org/ERIS/2/035006/mmedia) for further details on survey instrument, general respondent demographics, and summary statistics.

2.2. Mode choice modeling

Informed from collected data, a mode choice model was developed based on the multinomial logit model. This model is widely adopted across different applications of travel choice modeling. The model development in this study serves two needs: (i) gathering insights on the characteristics of the E-bike sharing program users, and (ii) providing a tool to predict the market share of E-bikes as a function of trip distance in presence of other competing modes.

Specifically, equation (1) shows the utility function associated with adopting mode of transportation m in a choice experiment k, and specific attributes of respondent i. Accordingly, equation (2) shows associated utility in presence of error ϵ:

$$V_{i,k}^{m} = f(\mathrm{TD}_k, \mathrm{SD}_i, \mathrm{O}_i) \tag{1}$$

$$U_{i,k}^{m} = V_{i,k}^{m} + \epsilon \tag{2}$$

where:

- TD_k refers to the trip distance in choice experiment k;
- SD_i refers to socio-demographic characteristics of respondent i, including income, gender, age, job, and availability of other modes of transportation; and
- O_i refers to other collected information on the respondents, such as environmental awareness and other rating questions in the survey.

If we assume the error term ϵ to follow the Gumbel distribution, we can formally formulate the probability of respondent i choosing mode of transportation m in choice experiment k as seen in equation (3)

$$P_{i,k}^{m} = \frac{e^{V_{i,k}^{m}}}{\sum_{j=1}^{J} e^{V_{i,k}^{j}}} \tag{3}$$

where j refers to alternative modes of transportation available.

Note that we train the model based on the split of 80% of all the concatenated trip data collected in the survey, and then we test on the remaining 20%. Details on model performance are provided in the following section.

2.3. Life cycle assessment

In modeling the environmental impacts of modal shifts triggered by E-bike usage, it is essential to have a unified analysis framework that quantifies various environmental impacts of different transportation modes during their use-phase. For this, we adopt the principles of WTW LCA. In general, LCA analysis has been widely adopted to evaluate different engineering applications and quantify their contribution to different environmental emissions [6, 34]. Current literature evaluates some environmental impacts of E-bike, through looking at the raw material and manufacturing (i.e., emissions due to bike manufacturing, battery manufacturing, etc). While such analysis is important in quantifying the environmental impacts, the use-phase environmental impacts remain a critical part to address. In transportation systems, use-phase environmental analysis entails quantifying emissions of different transportation modes taking into consideration the complete fuel cycle; from extraction until usage. It is important to note here, that the transportation system is naturally dynamic and depends on travel behavior and mode choices. When modeling use-phase environmental impacts of E-bikes it is critical to assess how the presence of E-bikes affects the usage of different modes of transportation, which will result in cascading impacts. Accordingly, linking both WTW LCA framework and modal shifts analysis presents a unique opportunity to holistically quantify the use-phase environmental impacts of E-bike sharing.

The system boundary of our WTW LCA analysis is shown in figure 1. The idea here is to estimate different environmental impacts of available modes of transportation by exploring emissions due to fuel extraction (or energy extraction in case of electric modes) and fuel/energy consumption during usage. To obtain estimates of the WTW environmental impacts, we use the Greenhouse Gases Regulated Emissions and Energy Use in Technologies (GREET) model [36]. The GREET model is the state-of-art in transportation LCA analysis. GREET quantifies various emissions factors of different transportation modes during their use-phase. In our work, there are six different modes of transportation which are of interest; personal vehicle, bus, ride-hail, E-bike, conventional bike, and walking. Accordingly, we use the GREET model to extract emission factors of these different transportation modes. Note that in our analysis we use the GREET tool to model the transportation modes of interest in a way that closely depicts those available in Madison. For instance, vehicles (personal vehicles and ride-hail vehicles) are modeled as spark ignition with internal combustion engines running on a mixture of 90% gasoline and 10% ethanol by volume (this specific mix is widely available in Madison), and assumed to carry only one person. Buses are modeled to depict those available in Madison: they are assumed to be compression ignition direct injection vehicles running on low sulfur diesel and carrying on average 13 people (based on observed ridership data). Conventional bikes and walking are not considered to have any use-phase environmental impacts, as we disregard any impacts due to human effort. However, the impact of these modes lies in altering the modal shifts. As for the E-bike, their environmental impacts are due to electricity generation and usage. They are assumed to consume an average of 10 WH/mile and are powered with electricity generated according to the Wisconsin state electricity generation mix. Consequently, five different environmental impact categories are used to gather broad insights into the environmental impacts of the transportation system. The literature focuses mostly on greenhouse gas emissions, yet we believe that other factors are also important to understand as they have more direct health consequences. The environmental categories are: energy consumption (kJ), greenhouse gas emissions (GHG, kg), particulate matter (PM2.5, mg), SO_x emissions (mg), and NO_x emissions (g). The environmental impacts are estimated per passenger mile basis and computed as the product of distributional transportation mode usage (i.e., mode splits) and extracted emission factors from the GREET model. These impacts are calculated for the observed modal shifts in the survey and different scenarios to be discussed in section 3. We further direct readers to the SI for more information on emission factors and modeling assumptions.

2.3.1. Limitations and boundaries

We deem it important to note that our environmental analysis incorporates only use-phase emissions as it mostly relates to modal shifts. It does not include emissions due to (i) manufacturing of the E-bike components (e.g., battery, steel frame, etc) and (ii) operational needs of an E-bike sharing program such as fleet rebalancing, maintenance and battery recharging. Fleet rebalancing refers to the practice where a special vehicle drives around the E-bike dock stations to recharge the battery and move E-bikes around stations to serve understocked stations. All these are accompanied by an environmental footprint that can have significant impacts.

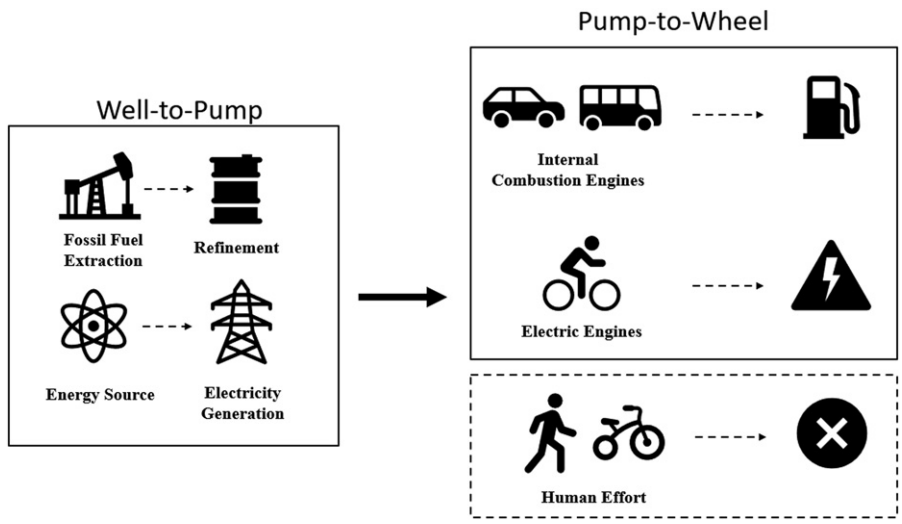

Figure 1. LCA—WTW system boundary for use-phase environmental impacts of E-bikes.

While few, some studies found that the emissions from manufacturing and operational needs of bike sharing systems can have a significant impact on overall environmental impacts. For instance [37], shows that bike rebalancing in a station-based bike sharing system can account for 36% of GHG emissions emitted by the system, and that optimizing bike rebalancing in a sustainable approach is important. A study on bicycle sharing in China shows that bike manufacturing contributes to negative environmental impacts [38]. A study on shared dockless electric scooters shows that around 43% of global warming impact of the sharing program can come from daily collection of scooters for charging and 50% of impacts come from materials and manufacturing [2].

We further detail some limitations of this study in section 4.2.

3. Results and discussion

3.1. Mode choice analysis: E-bike usage patterns

The mode choice model developed from survey observations allows us to gain an understanding into the users of E-bike and their potential competition with available modes. The formulated model is summarized in table 1. It is noted that the overall distribution of modal splits (i.e., all trips done by respondents) before joining the BCycle membership were: personal vehicle (42.5%), ride-hail (1.6%), bus (14.13%), E-bike (0%), conventional bike (12.76%), and walking (28.94%). However, after access to an E-bike with BCycle membership, the updated modal splits were: personal vehicle (35.91%), ride-hail (1.96%), bus (10.11%), E-bike (21.83%), conventional bike (8.63%) and walking (21.56%).

To gain more insights into the characteristics and travel choices of E-bike users, we analyze the various relationships in table 1 as it reveals potential users of E-bike. First, we analyze different attributes of E-bike users. It is noted that those aged between 18–30 were most likely (from a statistical point of view) to travel with an E-bike. Interestingly, and in accordance to the literature, those of higher age (41–50) were found also to be likely to switch from conventional bike to an E-bike, which might be attributed to the advantage of E-bike in relieving some of physical requirements of cycling. As for income status, it is found that those with income between \$10 000–\$25 000 were most likely to use E-bike. Further, those who own a personal conventional bike were less likely to use E-bike as compared to those who do not. Males were found to be more likely to use an E-bike as compared to females. Such behavior might be traced back to the impact of trip chaining and care giving responsibilities on women's travel patterns and mobility decisions [39].

Interestingly, those who noted cost effectiveness as their primary motive in using an E-bike were more likely to travel with an E-bike. This is rather interesting as it reveals an economical interest in the adoption of E-bike through a bike sharing program. However, the economical incentives between owning E-bike versus using an E-bike through bike sharing program remains an interesting topic and in need of further analysis, outside the scope of this work. Additionally, people with governmental jobs and those working in the restaurant and food service industry were more likely to use E-bike. This can be attributed to the locality of such types of jobs which typically are in the central business district, where amenities are close by and travelers do not need to travel far for their typical destinations. Finally, those who identified themselves as being extremely environmentally aware were more likely to use E-bike. This is an interesting observation in light of the ongoing

Table 1. Model estimation (p-value: 0^{***}, 0.001^{**}, 0.01^{*}, 0.05^{-}, $0.1^{\cdot}$, 1).

Coefficients	Estimates (std. error)					
	E-bike	Personal vehicle	Bus	Ride-hail	Walking	Conventional bike
Alternative specific constant						
Intercept	3.46 (0.98***)	1.91 (0.32***)	0.98 (0.02**)	2.05 (0.94*)	5.64 (1.41***)	Base
Generic modal attributes						
Distance (miles)	0.25 (0.008***)	0.31 (0.041***)	0.28 (0.04***)	0.29 (0.046***)	−0.60 (0.06***)	Base
Indicator variable						
Gender (base: male)	−0.28 (0.03 **)	−0.77 (0.21 ***)	−0.96 (0.3***)	−0.68 (0.29*)	−0.67 (0.05***)	Base
Age (base 18–20)						
Age: 21–30	−0.59 (0.18 **)	−0.53 (0.11**)	−0.26 (0.15$^{\cdot}$)	−0.39 (0.74)	−0.56 (0.38)	Base
Age: 31–40	−0.73 (0.51)	0.56 (0.03***)	−0.26 (0.57)	−1.1 (0.79$^{\cdot}$)	−0.43 (0.51)	Base
Age: 41–50	−1.36 (0.55***)	−0.57 (0.19**)	0.48 (0.51$^{\cdot}$)	−0.53 (0.91)	−0.98 (0.45**)	Base
Age: 51–60	−0.68 (0.53)	0.54 (0.21**)	−0.23 (0.31)	−0.24 (0.91)	−0.98 (0.5$^{\cdot}$)	Base
Age: 61+	−0.26 (0.60)	1.1 (0.53**)	2.27 (0.78***)	0.41 (1.2)	0.19 (0.61)	Base
Income in dollars (base: 10 000–14 999)						
Income: <10 000	−1.6 (1.2)	−3.2 (1.35*)	−1.8 (1.32)	−0.81 (1.47)	−1.38 (1.2)	Base
Income: 15 000–24 999	0.83 (0.21**)	−1.76 (1.22$^{\cdot}$)	−0.84 (1.4)	−0.01 (0.9)	−0.07 (1.23)	Base
Income: 25 000–34 999	−1.17 (0.8$^{\cdot}$)	−0.93 (0.53*)	−2.21 (1.5$^{\cdot}$)	−0.98 (2.1)	−0.53 (1.21)	Base
Job category (base: others)						
Restaurant, food & drink	0.57 (0.26*)	−1.12 (0.77)	−1.26 (1.1)	−0.81 (1.31)	0.31 (0.097*)	Base
Governmental	0.63 (0.32**)	−0.93 (0.49$^{\cdot}$)	−0.59 (0.83)	−1.54 (1.17)	1.13 (0.5^{-})	Base
Environmental awareness (base: extremely aware)						
Environmental awareness: not at all aware	−1.84 (0.78*)	5.46 (4.95)	−2.14 (1.86)	5.57 (4.94)	1.75 (0.79$^{\cdot}$)	Base
Availability of (base: no)						
Personal conventional bike	−1.31 (0.31***)	−1.46 (0.34***)	−1.36 (0.41***)	−1.95 (0.52***)	−1.26 (0.31***)	Base
Personal vehicle	0.46 (0.26$^{\cdot}$)	3.13 (0.32***)	0.29 (0.37)	−0.02 (0.53)	0.24 (0.21)	Base
Bus pass	−0.22 (0.23)	−0.47 (0.23^{-})	1.61 (0.42***)	−1.11 (0.43$^{\cdot}$)	−0.12 (0.23)	Base
Cost effectiveness rating	0.34 (0.093**)	NA	NA	NA	NA	NA
Quality of fit						
AIC	5201.885					
McFadden R2	0.308					
Number of observations	3152	80% training				
Number of participants	450					

efforts of individuals and cities to move into more environmentally friendly modes of transportation. However, it is important to note that these observations remain a short term insight as travel behavior constantly evolves and adapts with the emergence of new technologies. Also, we note here that a survey questionnaire by BCycle in 2020 to their users, shows that 78% of their respondents where first time users of an E-bike, and 49% (47%) of their users are female (male).

3.1.1. Model predictive performance

Other than revealing characteristics of users of the E-bike sharing program, the mode choice model could be a useful tool to predict the market share of competing modes of transportation for different modal characteristics $V_{i,k}^{m}$ (as expressed in equation (1)). This comes naturally through the mathematical characteristics of the mode choice model as it reveals the distribution of mode choices for a population under study. Accordingly, we provide some insights on the predictive performance of the model and expected error.

After training the model with 80% of the total data points collected (note each data point corresponds to a trip done by an individual), we test the model's predictive performance on the remaining 20%. Table 2 shows the expected error rate in the model. An error here refers to the model misclassifying the mode of transportation, and thus the error rate is the probability of the model making an error in classification. For instance,

Table 2. Model prediction error.

	Error rate	Predicted mode					
		Personal vehicle	Ride-hail	Bus	Conventional bike	E-bike	Walking
True mode	Personal vehicle	**1**	0.007	0.034	0.075	0.130	0.034
	Ride-hail	0.086	**1**	0.314	0.029	0.086	0.029
	Bus	0.175	0.000	**1**	0.100	0.125	0.150
	Conventional bike	0.107	0.000	0.036	**1**	0.125	0.214
	E-bike	0.088	0.022	0.077	0.055	**1**	0.209
	Walking	0.276	0.013	0.039	0.132	0.421	**1**

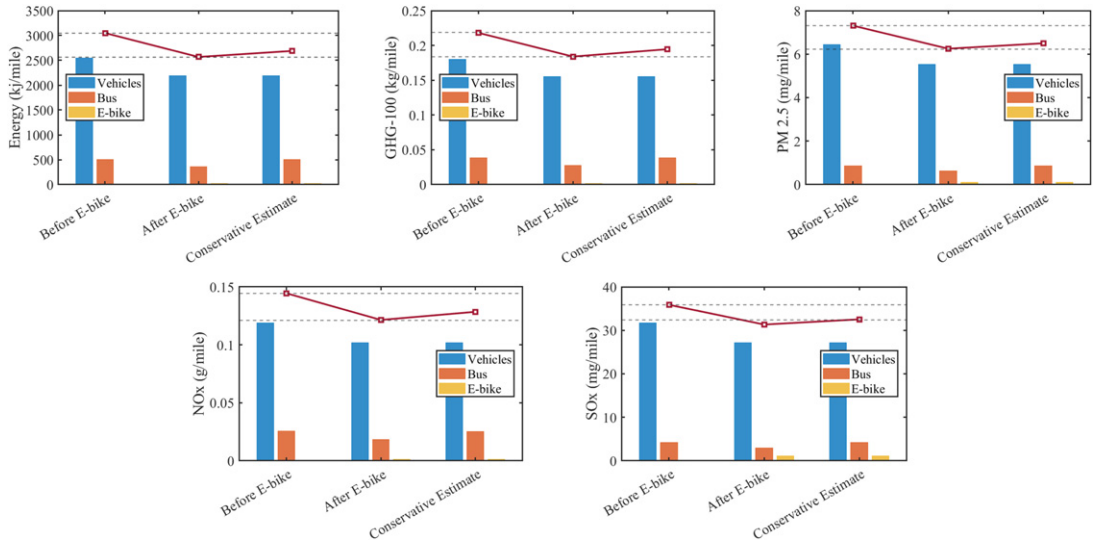

Figure 2. Environmental impacts before and after E-bike. Red Line represents the total environmental impacts: sum of impacts from each mode. Vehicles represent personal vehicle and ride-hail modes.

table 2 reveals that the probability of error is particularly higher in scenarios where walking is a probable mode of transportation, as misclassifications among walking, personal vehicle and biking (both conventional and E-bike) are the highest. Generally, it was seen that the expected error rate in the model is ≈34%. We note that this error is relative to the six levels of predictions (i.e., the six mode choices: personal vehicle, ride-hail, bus, conventional bike, E-bike, and walking). Thus, the overall error is the summation of prediction error in each. Because of the larger number of mode choices, the model's complexity increases significantly.

3.2. Environmental impacts analysis

In this section, we analyze and quantify the use-phase environmental implications of the E-bike sharing program. Specifically, we analyze three key points: (i) overall environmental impacts caused by modal shifts triggered after users had access to E-bike membership, (ii) the influence of trip distance on the E-bike sharing program's ability to compete with different modes of transportation and the respective environmental implications, and (iii) the impact of the energy infrastructure adopted.

3.2.1. Overall environmental impacts: before and after access to E-bike sharing

The environmental impacts as a result of modal shifts triggered by E-bike sharing, is shown in figure 2. A comparison between the 'before E-bike' and 'after E-bike' cases, shows a decrease in use-phase environmental impacts (per passenger mile) across all studied categories. E-bikes are shown to be an attractive mode of transportation that travelers are likely to use. This leads to a migration of modal usage away from carbon-intensive modes towards the environmentally desired E-bike. In fact, the survey data reveals that trips that were previously done by other modes and were replaced by an E-bike: around 30% of them were previously done by personal vehicle, 19% by bus, 16% by conventional bike and 33% by walking. Clearly the migration of users away from carbon-intensive modes (i.e., vehicles, and buses) is beneficial from an environmental perspective. However, E-bikes can also replace conventional bike and walking trips which increases emissions. This phenomenon is analyzed more in section 3.2.2.

We further show an additional 'conservative estimate' case in figure 2. This case refers to realistic situations where the migration of users away from the bus does not necessarily negate the environmental emissions of

Table 3. Environmental Impacts as a result of modal shifts before and after E-bike. Note: negative sign refers to a decrease in emissions.

Environmental impact	Change (%)
Energy consumption (kJ/mile)	−15.78%
GHG-100 (kg/mile)	−15.92%
PM2.5 (mg/mile)	−14.44%
NO_x (g/mile)	−15.89%
SO_x (mg/mile)	−12.61%

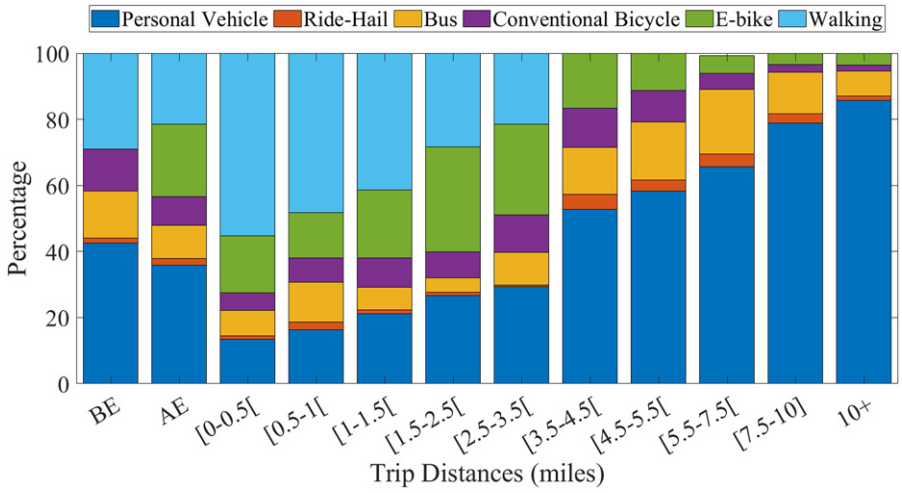

Figure 3. Modal share distribution for different scenarios. Note that the bracketed values in the *x*-axis represent the lower and upper bound, respectively, of the trip length. BE refers to 'before E-bike' and AE refers to 'after E-bike'.

the bus. The basic idea is that buses would still be expected to operate and maintain their regular routes even if some of their users shift toward E-bike. Nonetheless, as the results show, we still expect environmental benefits with the presence of the E-bike sharing program. The expected change in environmental emissions between the 'before E-bike' and 'after E-bike' cases is presented in table 3.

3.2.2. Distance based scenarios and analysis

Trip distance plays a critical role in the analysis of environmental impacts of E-bikes. This is rather expected as the mode choice model revealed trip distance as a statistically significant factor in the respondent's decision to choose an E-bike. This is also consistent with previous literature on cycling behavior [29, 30]. The main idea is that travelers are most likely to use an E-bike when distances are relatively short and would adopt other modes of transportation for longer distances. This is particularly interesting as E-bikes are an attractive mode of transportation in short distance trips and would compete with other available modes (bus, personal vehicle, walking and conventional bike). The caveat here is that when E-bikes compete with conventional bikes and walking, then it would increase the environmental emissions, as E-bikes inherently have some emissions due to their electrification. However, when E-bikes compete with personal vehicles, ride-hail and buses, then it would alleviate the environmental toll of energy-intensive modes.

To better understand the implications of trip distance on modal shifts in presence of E-bikes, we analyze the survey data based on different trip distance scenarios. Each scenario represents a set of trips done by respondents within a certain distance frame. The modal share distributions among the available modes in each scenario are then summarized in figure 3. Note that the modal distribution is a percentage measure, and since not all trip distance scenarios have the same number of trips, then there could be some magnifying of splits. However, the minimum number of trips in each scenario is 109.

Interestingly, one can notice the potential of E-bikes in competing with available modes (see green color in figure 3 across different trip distance lengths). However, the extent of E-bike's ability to attract users away from carbon-intensive modes varies with trip distance. For instance, in longer distance trips (e.g., ⩾5.5 miles), the E-bike sharing significantly loses its potential in competing for ridership. E-bikes are shown to be most competitive at trip distances between 0–2.5 miles. Within this frame, E-bikes pull travelers from various modes of transportation, which has a convoluted impact on environmental emissions. Specifically, while E-bikes replace vehicle/bus trips, they also replace walking and conventional bikes. This limits the environmental benefits of E-bikes because E-bikes consume electricity and thus generate emissions. Therefore, it is critical to analyze

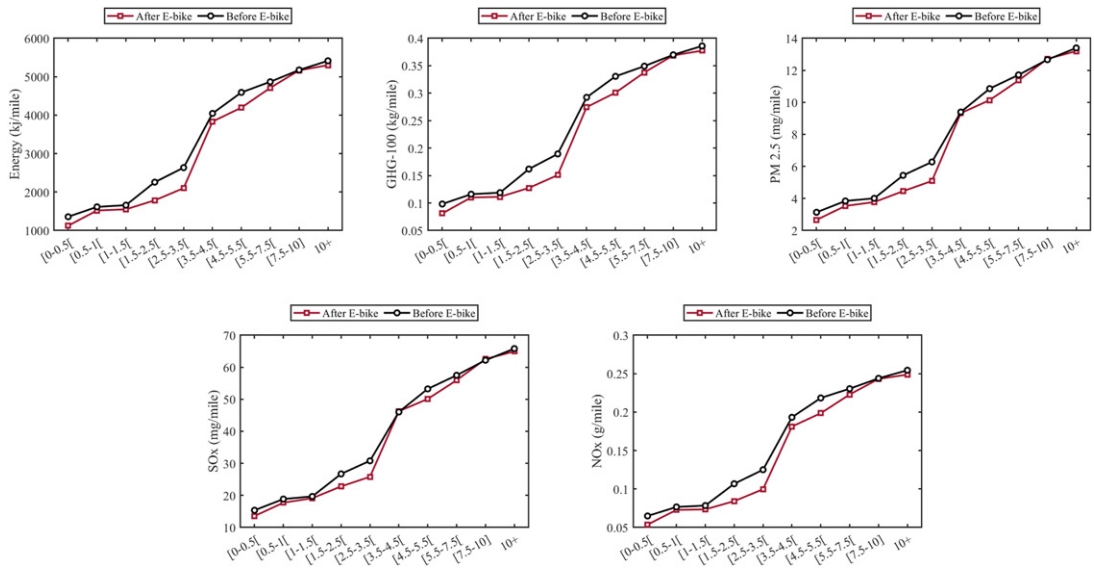

Figure 4. Total environmental impacts 'before E-bike' and 'after E-bike' as function of distance trips.

what modes they are replacing at different trip distances. The mode share data in figure 3 suggests that in short distance trips (0–0.5 mile) E-bikes are competing with walking and conventional bikes to a greater extent than they are with vehicles or buses. However, they start to compete more with carbon-intensive modes at (1–2.5 miles), and this is where they might reduce use-phase environmental impacts. Interestingly, E-bikes are better able to attract users away from carbon-intensive modes than walking or conventional bikes.

To better visualize the convoluted environmental impacts triggered by E-bike's competition with various modes of transportation across different trip distances, we plot the total environmental impacts 'before E-bike' and 'after E-bike', as seen in figure 4. We note that the total environmental impacts 'before E-bike' (black line in figure 4) are informed by the mode distribution analysis of the survey data. Interestingly, while the environmental impacts 'before E-bikes' are generally higher than those 'after E-bikes', there exists a disparity as function of distance. For instance, we see most reduction in environmental impacts in trip distances between 1–2.5 miles, and to lesser extent between 3.5–4.5 miles. However, the reduction in emissions is relatively small between 0–1 miles and approximately null for trip distances greater than 5.5. This could be traced back to the modal replacements triggered by E-bikes at different distances. For short distances, E-bikes could be replacing walking and conventional bicycles, rather than carbon-intensive modes. And at long distance trips, E-bikes are incapable of competing with carbon-intensive modes. Thus, the main environmental benefits are derived when E-bikes are capable of replacing personal vehicles, ride-hail, and buses.

3.2.3. The energy infrastructure and its impact

In the discussion of electricity dependent modes of transportation, the impact of the energy infrastructure is often neglected. The way electricity is generated (i.e., distribution of various energy resources needed to generate electricity) can alter the predicted environmental benefits. In section 3.2.1, we summarize in table 3 the overall expected environmental benefits as a result of accessing E-bike sharing program. However, to some extent the environmental benefits of E-bike are still dependent on the electricity mix usage to power them. This is of specific interest, as we have seen that E-bike could also compete with walking/conventional bicycle, which would add to the use-phase environmental impacts. Accordingly, in this section we study how the observed environmental benefits (as noted in table 3) would change if the electricity mix used in powering the E-bike changes. Figure 5 shows how the results in table 3 would change as a function of different electricity mixes. The electricity mix scheme used in this study is the one following the state of Wisconsin electricity generation resource distribution. A sample of different U.S. states is chosen, and their electricity mix distribution (as summarized by the Energy Information Administration), is used to simulate the behavior when E-bikes are powered by the corresponding mix. Indeed, the results indicate that the energy infrastructure plays a role in the benefits reaped from adopting an E-bike sharing program to some extent. States whose electricity generation mix is dominated by coal (West Virginia (88.4%), Kentucky (68.8%)) might experience less benefits. Specifically, when it comes to particulate matter (PM2.5), greenhouse gas (GHG-100) and nitrate (NO_x) emissions. Others, such as California, Connecticut, Oklahoma, who are more reliant on cleaner energy (as natural gas, solar, wind, etc) can reap further benefits. An interesting case here is New Hampshire, which has a 59% dependency on nuclear energy and merely (0.8%) on coal energy, might still observe lower benefits in different

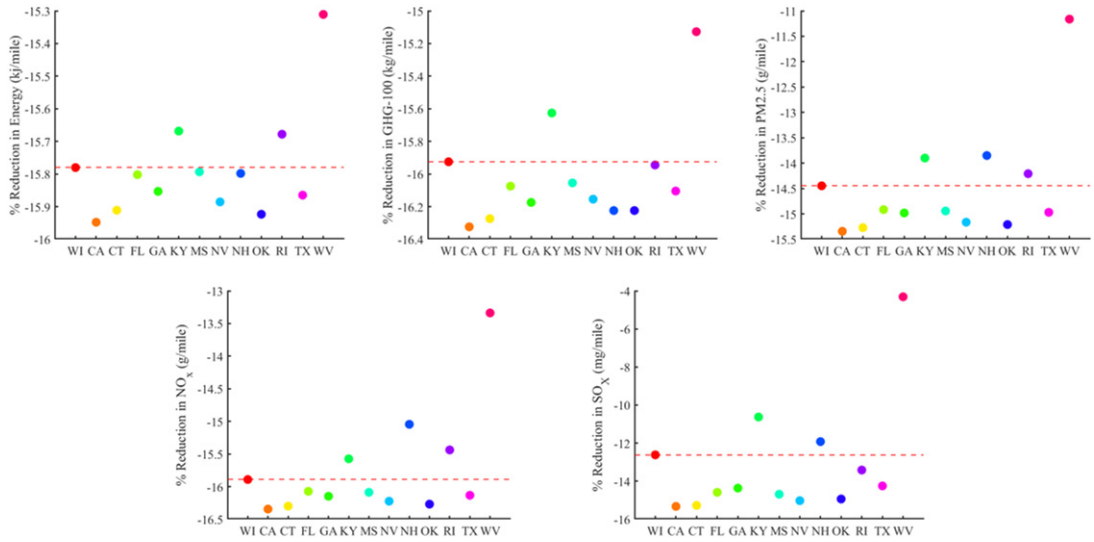

Figure 5. Impact of electricity mix distribution for different states on observed benefits seen in table 3.

environmental categories (nitrate and sulfate emissions). This stresses on the importance of analyzing multiple emission factors to have a systematic view at environmental impacts of the transportation system.

4. Conclusions, limitations and future needs

4.1. Conclusions

In this work, the adoption of E-bike through a bike sharing program is analyzed and its respective impacts on use-phase environmental factors is quantified. A holistic framework is adopted to link E-bike usage patterns and its potential in altering modal distribution. Accordingly, use-phase environmental analysis based on WTW emission factors is used to estimate the environmental benefits. It was found that the E-bike enjoys a level of attractiveness as a viable mode of transportation. This allows it to compete with other carbon-intensive modes of transportation (personal vehicles, buses), and cause a migration of trips in its interest. Specifically, it was found that E-bikes are most competitive in short distance trips. However, in those distance trips they also compete with walking and conventional bike, which does not lead to environmental benefits. Yet, they are better able to compete with carbon-intensive modes at longer distances (1–2.5 miles), which was found to lead to a beneficial impact by reducing use-phase transportation emissions across five different categories. At longer distance trips their usage rate drops significantly for other modes (vehicles and buses). Additionally, the impact of energy infrastructure on the environmental benefits is explored. The way electricity is generated to power the E-bike, plays a role in environmental benefits observed.

At the current state, E-bikes enjoy rigorous efforts by cities to move into more environmentally friendly modes of transportation and the booming popularity of bike sharing programs. This provides a unique opportunity for stakeholders to introduce environmentally desired modes of transportation, however it is essential to steer their deployment in ways that match travel behavior and trip requirements. This comes with a unique challenge in building an effective, safe, accessible and energy efficient bike sharing platforms with E-bike at their core.

4.2. Limitations

While this study serves as a step forward in analyzing E-bike sharing usage in the U.S. and their environmental impacts, several limitations are noted. First, our environmental analysis focuses on use-phase impacts while neglecting emissions due to manufacturing of these E-bikes or due to operational needs. For instance, an E-bikes sharing program requires regular operational work for changing batteries, shifting placements between stations, etc. All these would result in environmental emissions and thus can alter the overall impacts. We have discussed previously in section 2.3.1 some potential implications of manufacturing/operations related emissions in bike sharing programs, informed by similar literature. The extent of these implications can vary depending on the size of the bike sharing program, the city it is operating under, the sustainable approach for optimizing their fleet, etc. In this work, we do not quantify the exact emissions due to our focus on use-phase emissions. This remains an important area for future research on docked E-bike sharing programs. Second, our survey study is constrained in its geography, size and scope. For instance, we only collect data from membership

users of BCycle in the City of Madison, Wisconsin. This could limit generalization of the results to other regions in the U.S. Further, we do not consider the impact of weather on the usage of E-bikes, which is likely to bring significant changes. Third, the conclusions from the mode choice model remain rather short-sighted and are subject to change as users dynamically change their mode choice behavior. Additionally, the model's predictive power could be enhanced with more data (e.g., travel diaries).

4.3. Future needs

It is critical to continuously carry out longitudinal studies (i.e., with time) on how E-bikes usage is changing and its ability to compete with other modes. Such analysis can provide stakeholders (i.e., programs as BCycle) the ability to rethink the deployment and development of E-bikes in ways that maximize usage and thus environmental benefits.

Acknowledgments

This work was supported by a grant (CTEDD 020-04) from the Center for Transportation Equity, Decisions, and Dollars (CTEDD) funded by U.S. Department of Transportation Research and Innovative Technology Administration (OST-R) and housed at The University of Texas at Arlington. This work has not been formally reviewed by the sponsors and reflects the opinions of the authors.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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