Examining the adoption of electromobility concepts across social contexts for energy transition

Julia Köhlke
OFFIS e.V.

Adam Lechowicz
University of Massachusetts Amherst

Oluwole Fabikun
University of Massachusetts Amherst

Noman Bashir
Massachusetts Institute of Technology

Abel Souza
University of California Santa Cruz

Prashant Shenoy
University of Massachusetts Amherst

Sebastian Lehnhoff
OFFIS e.V.

ABSTRACT

The impact of mobility decisions not only shapes urban traffic patterns and planning, but also its associated effects, such as greenhouse gas (GHG) emissions. Although e-bike sharing is not a new concept, it has shown significant strides in technological progress in recent years due to the ongoing process of digitalization, specifically towards decarbonization effects. Past studies have shown that e-bike sharing shows a potential as a fast, mobile, and environmentally friendly alternative to cars and public transport. Although e-bikes represent a viable alternative to traditional means of transportation, there is a lack of quantification in understanding the impact and acceptance of e-bikes towards social contexts as well as its adoption as a type of sharing concept. In this paper, we employ the Unified Theory of Acceptance and Use of Technology (UTAUT) model as an analytical framework to discern the use and acceptance of e-bike sharing as an emerging technological concept across different cities and social contexts. Our findings reveal that the e-bike sharing system's utilization is skewed towards a small percentage of "frequent users", and overall usage is biased towards younger, more-educated, and higher-income populations who live in bike-friendly areas. Our work contributes to the feasibility of embedding the e-bike sharing concept in the scope of the energy transition.

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1 INTRODUCTION

In 2023, transportation accounted for 38% of energy-related greenhouse gas (GHG) emissions [2] in the United States. Of this, 40% is estimated to be contributed by *urban mobility*. Global trends towards urbanization and subsequent increases in population density have underlined this contribution – Urban mobility demand is projected to more than double by 2050 [10], magnifying the trend.

At the same time, the global surge in sharing concepts has significantly contributed to the success of sustainable mobility concepts. Electric-assisted bicycle (e-bike) sharing plays a pivotal role in promoting sustainable joint use of resources [3] and has gained popularity as a low-cost alternative to traditional taxis and personal cars, offering greater flexibility compared to public transportation [12].

In 2024, the broader bike sharing market size is estimated at USD $9.47 billion [13]. E-bike sharing currently makes up about a quarter of this market [6], and this share is expected to increase in the coming years. This expansion simultaneously paves the way for new entrants into the market [3]. This trend is particularly notable in large cities, where substantial investments are being directed towards e-bike sharing concepts as a promising alternative for future mobility [11]. Overall, however, e-bike sharing concepts are still untested in terms of acceptance and usage across different societal contexts with regards to transition processes. Although many initiatives exist in the United States, e-bike sharing has not yet completely caught on as a serious alternative mobility concept.

In this paper, we evaluate and measure the effects of e-bike use and acceptance across different cities, and social contexts in New England. We use comprehensive data from ValleyBike Share spanning the years of 2018 to 2022. ValleyBike is an initiative created to encourage short bicycle journeys within communities, linking clusters of major employers, universities, shopping centers, tourist attractions, and local residents [9]. We investigate the profileration of this e-bike sharing system across diverse locations within a specific geographical region of the U.S. Within the operating region, each town is characterized by different population demographics as well as different infrastructural factors that may influence e-bike adoption. In evaluating the usage and acceptance of e-bike sharing, we answer the following questions:

(1)*: How is e-bike sharing used and accepted in diverse societal settings during the transition to more sustainable mobility concepts?*

(2)*: How is e-bike usage adopted over time and accepted as a new mobility concept?*

The analysis of acceptance and usage is of particular importance not only to identify trends for the development of new mobility concepts but also to derive possible consequences for future technological development, which is shaped in particular by society.

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2 BACKGROUND

New mobility concepts, such as e-bike sharing, are crucial for a successful low-carbon transition within the broader energy system. The prospective change to low-carbon takes place not only on economic or technical levels but also on a social one, motivating the conceptualization of a *socio-technical system*. This new system includes new technologies and business models, but also changing consumer practices, cultural meanings, and new public policies [4]. Recent debates on socio-technical transitions primarily consider the transition dynamics but also the inertia of radical innovations that occur with them. From this vantage point, transition processes are long-term, multi-dimensional, and co-evolutionary, taking place between open-ended uncertainties and potential public policies that also have a central role [5].

In general, user acceptance has been identified as a meaningful enabler but, equally, a difficult endeavor when implementing new technologies, especially in areas influenced by profound environmental changes due to digitalization. User acceptance can be defined as the willingness of users to endorse and adopt an innovative technology [8]. Consequently, it serves as an indicator of the success of the technology's introduction. While researchers claim that social acceptance is a powerful force for developing and diversifying new technologies, it is often insufficiently involved in implementing and developing new technologies [7].

A unified approach for identifying the acceptance and use of technology is given by the Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh [14]. The author constructs a model that synthesizes these different approaches to user acceptance in one unified perspective. UTAUT identifies four determinants of user behavior in technologies, namely performance expectancy, effort expectancy, social influence, and facilitating conditions [14].While the model is already more than 20 years old, it is still widely used today and has been validated across various contexts and technologies, demonstrating its flexibility and applicability in different settings For this study, it provides a comprehensive framework for understanding technology acceptance.

In the UTAUT model, performance expectancy refers to the "degree to which an individual believes that using the system will help him or her to attain gains in job performance. [14] This determinant is the strongest predictor of intention for technology usage and stays meaningful throughout all measurement points over time. The theory claims that performance expectancy is significantly interrelated with demographics of gender and age, whereby new gender schema theory does not always refer to biological sex, but to different gender roles and socialization processes that are influential throughout life [14]. Another determinant for technology usage is effort expectancy, which is defined as the "degree of ease associated with the use of the system." Effort expectancy develops mainly in the perceived ease of use of new technology and any related complexities. However, effort expectancy is mostly significant during first use and becomes increasingly inconsequential after more periods of extended and sustained use [14]. Social influence is defined as "the degree to which an individual perceives that people whose opinions are valued believe that he or she should use the new system." The authors argue that social influence relates to how individuals believe others will view them as a result of using technology.

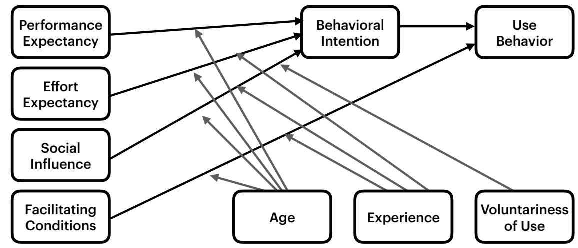

Figure 1: UTAUT Framework[1]

This means that the general surroundings influence an individual's choice of usage by constructing their norms, behavior, and attitude around technology [14]. Finally, facilitating conditions are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system." It is mainly related to internal and external constraints on behavior that users face in applying new technologies.

3 DESIGN AND IMPLEMENTATION

3.1 E-Bike model

We use data from the ValleyBike e-bike sharing system [9] as a case study to examine the utilization and acceptance of this technology in diverse social contexts. This initiative was a privately-operated effort that received public subsidies. Investment costs for similar e-bike sharing programs are estimated at around $600,000 USD and therefore rely on different funding sources. The system continuously operated in several cities of varying size in western Massachusetts from 2018 to 2022 (namely, the cities of Holyoke, Springfield, Amherst, Northampton, and Easthampton). Stakeholders including the technology manufacturer/operator, local governments, and local universities, were involved in its implementation and operation. The e-bike sharing network launched in 2018, featuring an initial deployment of 26 e-bike stations and 234 pedal-assisted e-bikes.

3.2 Our approach - UTAUT for e-bike sharing

Fig. 1 illustrates our approach, where we link several socio-technical factors with the e-bike sharing concept. For our purposes, it is necessary to define how UTAUT determinants can be technically represented in a data-driven manner, particularly in the context of the data availability from the e-bike sharing system. The technical data contains information about the records of the rides, such as usage frequency and the use of different stations. Data from 28,732 users and ~ 370,500 trips was collected over a five-year period from 2018-2022. Below, we connect the technical data of user behavior with the intended indicators for the UTAUT model, namely performance expectancy, effort expectancy, social influence, and facilitating conditions.

In our study, the main indicators were derived from the UTAUT model. We identified appropriate transferable translations of the four determinants as defined within the UTAUT framework that can be adapted to the e-bike model. This represents our unique interpretation of applying the UTAUT model to the e-bike concept. **Performance Expectancy** is a critical factor in e-bike adoption in terms of *trip frequency*. It refers to what users expect from e-bikes

[1] Adapted from the UTAUT model [14]

when using the technology. To identify e-bike adoption while minimizing external influence, we remove the impact of new stations, analyzing data based on only those stations available throughout the entire time series of the data, e.g., the oldest stations in each city. At the same time, we removed "ramp-up" and "ramp-down" periods from the data, because the e-bike sharing system was shut down in winter months. Hence, only the data from April 1 to October 1 was kept each year, representing the peak usage season. Regarding COVID-19's impact, the whole time series (pre- and post-pandemic) was examined to see whether COVID-19 impacted the e-bike sharing concept. The demographic variables of age and gender are mainly related to how often bikes are used regularly. We henceforth assume that if the e-bikes met the users' expectations, they are more likely to be used repeatedly. Likewise, the number of trips over time was calculated for each city.

Effort expectancy considers "user-friendliness" in terms of ease of use and effort required from the user. Our approach measures effort expectancy using the *trip duration*. For example, if the trips are too short, i.e., less than 5 minutes, we assume that people may be unlocking the bikes, finding their use difficult, and returning them to the same station. We note that if an e-bike user stops somewhere intentionally (e.g. running an errand) without docking the bike, the decreased average speed will complicate this effort expectancy analysis. Thus, we use the logged speed data for the bikes to identify intentional stops using a simple threshold technique (e.g., if the bike's is stationary for >10 minutes, we say the trip includes an "errand stop"). We find that roughly 2.17% of all trips have a stop like this, and we simply discard them for the effort expectancy analysis.

Social Influence concentrates the societal expectations within a demographic area, grounded in its perception of the technology's importance, utility or value. To ascertain the social influence, we evaluate whether users engage with the e-bike sharing system consistently and regularly. Specifically, we examine the *number of trips in combination with demographics* of these users and how it changed over time. Our approach for measuring the social influence is rooted in the social atmosphere of each city based on the population's demographics.

Facilitating Conditions includes several factors that may influence the use of e-bike-sharing systems. We measure it as the *number of trips against promoting factors in the specific area.* One such contributing factor is the availability of charging stations, with more stations leading to increased usage. Another factor is the availability of protected bike paths, where we would expect e.g., a positive correlation between the number of miles of bike paths in a town and the usage of e-bikes. We define the normalized *facilitating factors* of a town as (miles of bike path $\times$ number of stations)/population.

3.3 Subjective variables

To measure the acceptance and use of e-bike sharing within different social contexts, we use multiple subjective variables to identify their impact on e-bike use and acceptance, including median income, education (bachelor's degree or higher), median age, gender and voluntariness of use. We use U.S. Census data [1] to obtain the median income, education level, and age in each case study location. Finally, the voluntariness of use is an important factor in technology acceptance. When individuals feel they have a choice in whether or not to use a new technology, they may be more likely to adopt it. Based on the available data, including preferred e-bike routes, detailed bike maps, conclusions were drawn regarding the key factors, such as infrastructure.

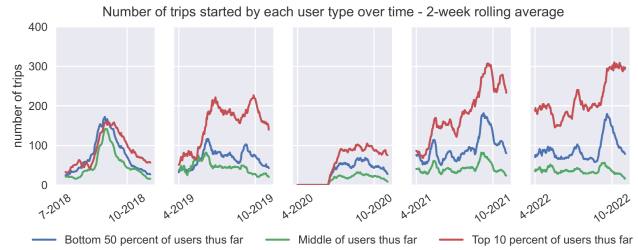

Figure 2: Performance Expectancy of E-bike Usage - System-wide number of trips

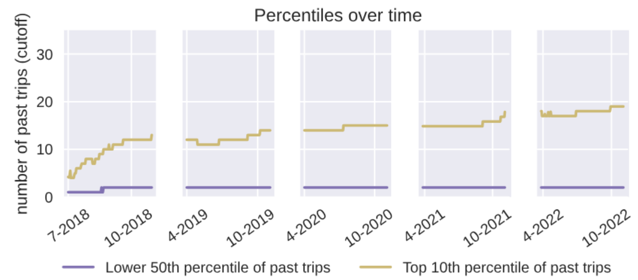

Figure 3: Performance Expectancy - System-wide no. of trips for regular (top 10%) and occasional (bottom 50%) users.

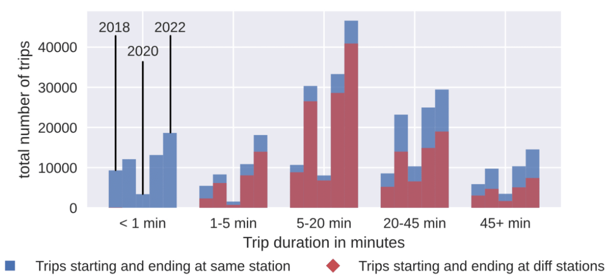

Figure 4: System-wide histogram of trip durations.

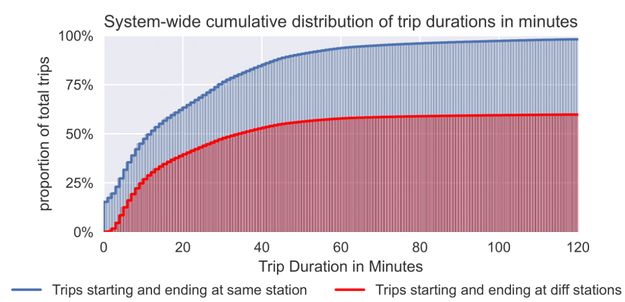

Figure 5: Cumulative distribution of trip durations.

4 EMPIRICAL RESULTS

For analysis, we use data from the e-bikes and their docking stations, along with publicly accessible census data. The e-bike data set provides information about each trip taken from 2018-2022, including the trip duration, starting and ending stations, and (anonymous) unique ID of the user. Each station in the network is located in one of the 5 cities under study, so Census data is integrated into our analysis by matching trips with the city in which they take place.

Results for Performance Expectancy: The first category of the UTAUT model shows how frequently e-bikes are used on a regular basis. For the analysis, we distinguish users based on percentiles – new users are represented by the – inclusive – bottom 50 percent of users, while heavy users are represented by the top 10 percent of users. When e-bike sharing was launched in 2018, the graph shows that usage for first-time users (users in the bottom 50th percentile) peaked initially at around 200 daily trips in September 2018.

At the beginning of 2019, the frequency of repeat users increased slowly. Year over year, there is a trend that the number of trips by repeat users increases up to 250 trips, while the bottom 50 percentile of users tends to decrease with a peak at 140 trips. Likewise, the middle users decrease with a number of 100 trips at peak. In 2020, the effects of the COVID-19 pandemic had a large impact on e-bike usage due to stay-at-home orders, as seen in the figure. E-bike usage restarted slowly in 2020 beginning in July, but did not reach the level of previous years. In 2021, the e-bike sharing system sees a resurgence, coinciding with the relaxation of COVID-19 restrictions. The trend shows that trips started by repeat users are rising sharply overall, with utilization peaking in September 2021. This trend is consistent in 2022, showing that repeated "heavy" users have the most trips, while new users or less frequent users have fewer trips.

Results for Effort Expectancy: To analyze the effort expectancy of the e-bikes, we analyzed the trip duration (i.e., the time elapsed from bike unlocking to redocking). Trip data spans July 2018 through October 2022. Using trip duration as a measure, Fig. 5 and Fig. 4 jointly illustrate the ease of e-bike usage, attributing the effort the users had to exert for their locomotion. Of particular interest here are short-term uses, especially those that take place for less than 5 minutes – for instance, the data set includes over 1000 trips that ended in less than 1 minute, returning the bike to the same station. In the early years of the bike share program, short trips (lasting between 1 and 5 minutes) typically returned to the same station. In later years, some of these short trips, despite brief duration, were between different stations. This trend may indicate an increase in the density of bike docking stations over time and an improvement in user experience, resulting in more efficient (faster) trips.

Results for Social Influence: Regarding the relation of the median income with the number of trips, a rough trend can be recognized in the data that the higher the median household income, the higher the normalized number of trips. For example, in Holyoke and Springfield, both the median income and the number of trips are lower. Amherst is a clear outlier with respect to this factor, especially in comparison to Easthampton, which has almost the same median income – the number of normalized trips in Amherst is significantly higher than Easthampton. A strong trend can be equally seen in the correlation between the normalized number of trips and the education of the population. With increasing education (in terms of a bachelor's degree or higher), the amount of trips increases. Finally, plotting the normalized number of trips against the median age in a city, we find that the lower the median age, the higher the number of trips in general. An exception is Northampton, where the number of trips is high despite a median age of 40.

Results for Facilitating Conditions: A notable outlier in terms of facilitating conditions is Northampton, driven by both a significant number of stations and strong bike path infrastructure. Interestingly, although Northampton has the strongest facilitating conditions by a significant margin, the normalized number of trips are higher in Amherst, which is a distant second in terms of facilitating conditions. On the other extreme of the graph, the other towns all have fairly low facilitating conditions. Notably, Holyoke is an exception. Despite very low facilitating conditions (explained mostly by a lack of bike path infrastructure), adoption as measured by the number of trips is comparatively high.

5 DISCUSSION

The introduction of e-bikes into the energy and mobility system of the U.S., particularly in Massachusetts, represents a *whole system change*. The findings show that the tradtionally car-centric U.S. has started adopting e-bikes as an innovative technology and alternative mode of transportation. A rising number of users over time indicates that the technology is experiencing promising growth in adoption, despite tempering effects due to the COVID-19 pandemic.

Performance Expectancy: Results indicate that performance expectancy is particularly met by regular users, whose numbers have increased over time. The technology is especially beneficial to the top 10 percent of users, which accounts for the overall increase in regular use. During recovery from the COVID-19 pandemic (i.e., 2021 and 2022) the overall number of trips rose significantly, with a peak in September. However, comparing just 2021 and 2022 to each other, they show similar trend without further increases, suggesting a saturation among highly regular users. The behavior of non-frequent users implies that the technology is likely to be tried out, but not necessarily used again. This could implicate that for most users, there is not an overall acceptance of the system e.g., for routine usage. However, it can also be interpreted that the technology is useful to the smaller proportion of users that are using it regularly. Nevertheless, there is also a slight overall increase in irregular users with only a few trips. The percentile cutoffs in Fig. 3 confirm these observations of the overall increase in usage. The momentary downward trend in 2019 can be explained by an influx of new users joining, offsetting the stable returning users.

Effort Expectancy: The results for effort expectancy show that irrespective of the trip duration, a significant number of trips started at one station and ended at another station. Since the stations are not close to each other, this indicates that users used the bike for a concrete purpose, such as commuting or traveling. In addition, Fig. 4 shows that the characteristics of the e-bike *trip duration* changed over the four years. While in 2018 short trips started and ended mostly at the same station, in 2022 short trips mainly ended at another station. Similarly, the data showed that trips from one station to another are not necessarily only for leisure – e-bike users increasingly use them for useful errands. Across all years, the most common trip duration is between 5-20 minutes, and this is also the category of trip that sees the greatest growth over 2018-2022.

Social Influence: From the demographics, we could interpret that cities with higher educational attainment place more emphasis on environmental protection, the use of green technologies, and physical activity. Therefore, it could be assumed that there is a higher

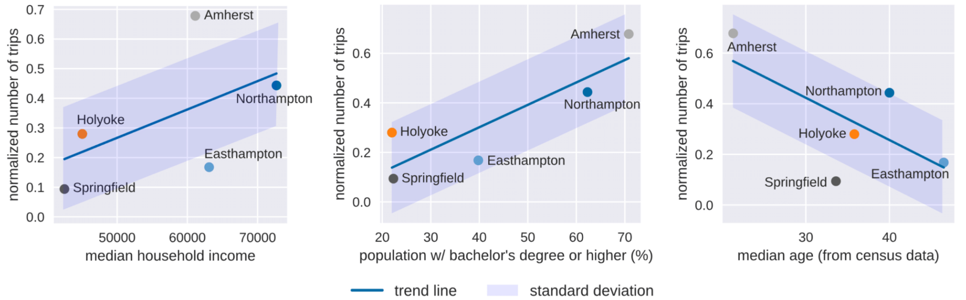

Figure 6: Social influences on e-bike sharing usage of across communities in our case study. R^2 scores for the trend lines are 0.2735 for income, 0.7585 for bachelor's degree, and 0.4415 for age, respectively.

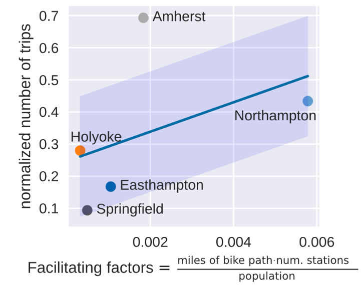

Figure 7: Facilitating conditions using system-wide no. of trips. R^2 score for trend line is 0.1874.

awareness of the e-bike system in these cities and that they are more likely to be championed by their governments. Northampton and Amherst are two examples that illustrate this particularly well. **Facilitating Conditions:** Facilitating factors such as the presence of bike paths and docking stations had a great influence on usage and adoption in the different cities. Most notable, cities with many bike paths had a higher adoption of the e-bike system within their town. For instance, university students showed high usage, likely helped by the bike paths on campus. We note that these facilitating factors are correlated with some other factors such as education and median income. This suggests that the infrastructure is generally very important and a valuable facilitating factor for the technology.

In conclusion, while e-bike sharing has the potential to offer many benefits, there are several challenges to be addressed. These include increasing complexity of governance, effectiveness of current strategies, and issues related to connectivity and accessibility.

6 CONCLUSION AND OUTLOOK

The success of e-bike sharing as an emerging mobility concept is contingent upon the technology meeting users' expectations, being equally accessible to all social groups, being suppored by its social surroundings, and having conducive facilitation conditions for its usage. The paper showed an analysis of the usage and acceptance of e-bike sharing as a new mobility concept in different demographic areas in Massachusetts, USA. For this purpose, the paper used the UTAUT model as an analytical framework to measure the performance expectancy, effort expectancy, social influence, and the facilitating conditions of e-bike sharing. Discussing various implications of e-bike sharing for the socio-technical transition of the energy system, our study reveals that a mobility concept can only be successful if the use of an e-bike can easily facilitate useful tasks (e.g., shopping) or be easily combined with other means of transport and therefore interact with existing systems. To conclude, e-bike sharing has the potential to become an essential pillar in a growing urban ecosystem of sharing, an important mobility concept, and a component of the energy transition.

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