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Article

Promoting Sustainable Urban Mobility: Factors Influencing E-Bike Adoption in Henan Province, China

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Abstract: This study examines the key factors influencing E-bike adoption and explores how advancing E-bike usage in Henan Province, China, can foster sustainable urban transportation and contribute to urban environmental preservation. Utilizing data from an online survey, binary logistic regression analyzes the impact of socio-demographic characteristics, perceived advantages, neighborhood environmental attributes, and vehicle ownership on E-bike usage. Findings indicate that socio-demographic factors, such as family size and occupation, significantly influence adoption, with workmen more likely than office workers to choose E-bikes. Cost savings emerged as the primary motivator for E-bike use, overshadowing environmental concerns, which unexpectedly negatively affected usage patterns. However, the presence of supportive infrastructure—particularly charging stations and dedicated lanes—proves crucial for promoting E-bike usage, highlighting the importance of accessible, environmentally supportive urban design. Vehicle ownership characteristics further illuminate how access to E-bikes correlates with regular usage. These findings suggest that, beyond cost-efficiency, targeted awareness campaigns and strategic infrastructure improvements are essential for embedding E-bikes into sustainable urban transport systems. By fostering adoption and supporting E-bike infrastructure, cities can significantly reduce urban pollution, improve air quality, and advance toward sustainable mobility goals in Henan Province and beyond.

Keywords: binary logistic regression; E-bike adoption; environmental benefits; sustainable urban mobility; vehicle ownership

1. Introduction

Sustainability has been widely accepted since the olden days, and today, the international community places great emphasis on its importance. Sustainability-focused institutions, such as the United Nations, are committed to advancing global economic and environmental sustainability goals [1]. The Environmental Performance Index (EPI), developed by Yale University and Columbia University, serves as a valuable tool for assessing a country or region's ability to maintain favorable environmental conditions for future generations [2]. In the 2024 EPI, which evaluates 180 countries using 58 indicators across 11 issue categories—covering climate change mitigation, air pollution, waste management, fisheries and agricultural sustainability, deforestation, and biodiversity protection—China ranks 154th [3]. This relatively low ranking highlights significant challenges in key environmental performance areas. Specifically, China ranks 168th out of 180 countries in the Air Quality category, which assesses the environmental impacts of air pollution [4]. This critical ranking

underscores the severe challenges China faces in managing air quality. Additionally, the May 2024 national air quality report revealed that 10 out of the 20 lowest-ranked cities for air quality, among 168 key cities, were located in Henan Province, accounting for 50% of the bottom rankings [5]. This high concentration of cities with poor air quality demonstrates the urgent need for comprehensive air quality improvement measures in Henan Province.

The escalating emissions from China's public transportation sector have intensified environmental concerns, prompting the need for sustainable alternatives. Among these, electric bikes (e-bikes) have emerged as an effective solution, helping to alleviate traffic congestion, enhance environmental quality, and promote public health [6–8]. When compared to motorcycles and automobiles, e-bikes generate substantially fewer pollutants per kilometer, with emissions reduced by several magnitudes [9]. Moreover, they consume 90% less energy and release 86–95% fewer pollutants than private cars [10], contributing to a significantly lower environmental health impact [11]. Beyond their environmental benefits, e-bikes provide notable health advantages, emitting considerably less carbon dioxide than cars over equivalent distances [12]. This makes e-bikes a promising approach for mitigating greenhouse gas emissions within regional passenger transport systems [13]. Renowned for their low carbon emissions and health-enhancing features, e-bikes play a pivotal role in improving urban air quality and offer a sustainable, active mode of transportation [14–17].

The growing adoption of e-bikes is playing a pivotal role in transforming transportation patterns across China [18]. In several cities, the suspension of new motorcycle license issuance, alongside bans on motorcycles and scooters in key areas, has fueled the expansion of the E-bike market [19]. Users of e-bikes undertake significantly more trips compared to traditional bicycle users [20]. In recent years, E-bikes have increasingly replaced buses, cars/taxis, and bicycles as the preferred mode of transportation [21,22]. China leads globally in both E-bike production capacity and market demand [23], with over one-third of consumers (34%) participating in the E-bike market [24]. In 2022, Henan Province had 45 million E-bikes, ranking second nationwide, closely behind Shandong Province. Additionally, Henan ranked second in E-bike ownership per 100 households, following Jiangsu Province [25]. The widespread adoption of E-bikes in Henan underscores their vital role in promoting environmental sustainability, positioning E-bikes as key contributors to sustainable urban transport and significant improvements in air quality.

This study is conducted within the geographical context of Henan Province, which holds one of the highest e-bike ownership rates and ranks among the top pollution levels in China. The findings, however, extend beyond the boundaries of Henan and offer valuable insights applicable to other cities in China and beyond. With many urban areas across China facing similar environmental challenges, such as air pollution and traffic congestion, the strategies and policy recommendations outlined in this research can serve as a reference for promoting e-bike adoption on a national scale. Furthermore, the implications of this study are not limited to China; cities worldwide grappling with the dual challenges of environmental sustainability and urban mobility can also draw on these findings to accelerate the development of e-bikes as a cleaner and more efficient transportation option.

A significant contribution to the existing literature on e-bike usage is made by adopting a comprehensive multi-dimensional framework in this research. Unlike many previous investigations that primarily focus on socio-demographic factors, this approach encompasses a broader range of influences, including perceived benefits, neighborhood infrastructure, and vehicle ownership characteristics. Notably, cost savings are highlighted as a crucial driver of e-bike adoption—a factor that has often been overlooked in prior studies. The findings emphasize the critical role of supportive infrastructure, offering actionable insights for Chinese cities striving to foster sustainable transport systems. By exploring the factors that influence e-bike usage, this research enhances the knowledge base in the field and provides valuable policy recommendations based on its findings. Specifically, it seeks to address the following two research questions:

1. Who are the electric bike users in terms of socio-demographic background in Henan province, China?

2. What are the factors that affect an individual’s decision to use an electric bike in Henan province, China?

To understand the circumstances under which E-bike users choose to ride, a survey was conducted with respondents aged 16 and older residing in Henan Province, China. The primary objective is to identify the factors influencing individuals' decisions to use E-bikes in Henan. Bivariate analysis will be applied to address the first research question, while econometric analysis will be employed to resolve the second. The rest of the structure of this paper is as follows: Section 2 reviews relevant literature. Section 3 outlines the proposed models and data used in the analysis. The statistical results are presented in Section 4. Lastly, Section 5 offers a summary of the key findings and conclusions.

2. Literature Review

2.1. Empirical Literature of Electric Bikes

Previous studies have examined a wide range of factors influencing e-bike usage, with Table 1 providing a summary of representative studies focused on e-bike or bicycle adoption. This table outlines key information regarding the study sample, location, method of analysis, and the aims of each study. Figure 1 delves deeper into specific influencing factors, including socio-demographic characteristics, perceived advantages of e-bikes, neighborhood environment attributes, and vehicle ownership characteristics. Various survey methodologies have been employed to collect data on the popularity and usage patterns of e-bikes. However, there remain notable gaps in the specific motivations and research methods of distinct user groups across different geographic contexts.

In Nanjing, two distinct studies have examined factors influencing e-bike usage. One study, based on 1,053 surveys from both e-bike users and non-users, evaluated the relationship between transport mode choice and the motives behind e-bike adoption [23]. Another study assessed the role of environmental awareness in the commuting mode choices of 1,729 e-bike users in Nanjing [26]. In smaller cities, research in Ganyu County, China, analyzed 1,800 questionnaires from educational institutions to assess how the built environment influences commuting mode choices [27]. Meanwhile, a study conducted in Shaoguan used logistic regression to analyze 441 face-to-face questionnaires, offering deeper insights into factors affecting the adoption of shared e-bike services [28]. These four studies highlight specific factors impacting e-bike users in China. Additionally, a nationwide study in 2022 utilized snowball sampling techniques to collect data from 507 e-bike riders, identifying key determinants influencing the adoption of e-bikes across China [1].

Multiple international also studies have investigated the factors influencing e-bike use across various regions. Notably, some studies employed logit models to explore key determinants [29,30], while others utilized descriptive analysis to profile user characteristics and mobility patterns [22]. Additionally, some research relied on historical data or meta-analytical approaches to assess e-bike ridership and mode substitution effects [6,31].

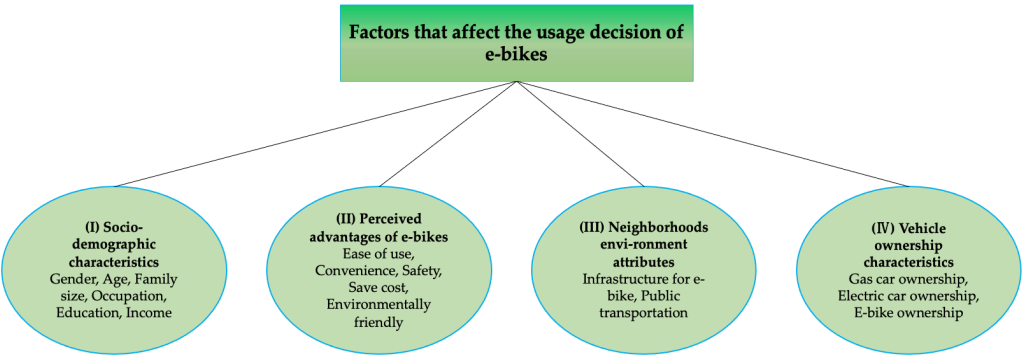


Figure 1. Factors that affect the usage or ownership of bicycles or e-bikes considered by the empirical studies.

Table 1. List of empirical studies regarding factors that affect the usage of bicycle or electric bike (e-bike).

Authors	Location	Data and Sample	Method of Analysis	Aim of the Study
Yasir et al. (2022) [1]	China	507 Chinese e-bike riders (snowball sampling technique)	Structural equation modeling	To identify factors influencing electric bike adoption.
Bigazzi & Wong (2020) [6]	Around the world	24 published studies across various global regions	Meta-analysis	To examine the mode substitution effects of e-bikes.
Astegiano et al. (2015) [22]	Ghent, Belgium	Online survey (100 e-bike users)	Descriptive analysis	To profile e-bike users and their mobility patterns.
Lin et al. (2017) [23]	Nanjing, China	1,053 surveys (e-bike users and non-users)	Logit model	To assess the link between transport mode choice and e-bike adoption motives.
Bai et al. (2020) [26]	Nanjing, China	1,729 commuters traveling by e-bikes	Mixed multinomial logit model	To assess the role of environmental awareness in e-bike users' mode choices.
Hu & Sobhani et al. (2021) [27]	Ganyu, China	1,800 questionnaires in educational institutions	Nested logit model	To evaluate the impact of the built environment on commute mode choice.
Li & Sinniah et al. (2022) [28]	Shaoguan, China	441 face-to-face questionnaires from shared e-bike users	Structural equation modeling	To better understand factors affecting the intention to use shared e-bike services.
Timpabi et al. (2021) [29]	Tamale, Ghana	439 adults (semi-structured questionnaire)	Logit model (1 = bicycle rider)	To explore factors influencing bicycle ownership and ridership.
Arsenio et al. (2017) [30]	Águeda, Portugal	2,232 students (aged 15-21 years)	Econometric analysis (logit)	To investigate determinants of students' e-bike usage for school commutes.
He et al. (2019) [31]	Park City, Utah, USA	Historical trip data from Summit Bike Share	Logit and Poisson models	To explore determinants affecting ridership in e-bike sharing systems.

Simsekoglu et al. (2019) [32]	Norway	Online survey (910 e-bike users and non-users)	Structural equation modeling	To explore factors influencing e-bike use in Norway.
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2.2. Socio-Demographic Factors

Numerous studies have investigated the socio-demographic characteristics influencing e-bike usage, focusing on gender, age, occupation, education, income, and family size. In terms of gender, findings have been somewhat inconsistent. Most research indicates that e-bike users are relatively evenly distributed between genders, with studies reporting a nearly 50% split between male and female riders [20–23]. However, some studies suggest a higher likelihood of e-bike usage among males compared to females [8,26,28], while little study has reported that females are more inclined to use e-bikes [27]. With respect to age, e-bike users are typically younger adults, with most studies indicating that the majority of riders are under 40 years old [21,23,26,28]. However, some research has highlighted the popularity of e-bikes among middle-aged individuals, particularly those aged 41 to 60 [22,33]. In comparison to traditional cyclists, e-bike users tend to be older, with an average age difference of several years [8,34].

Regarding occupation, many studies have found that as economies develop, e-bikes have become steadily adopted among the working class. E-bike users are predominantly young commuters, especially office workers [21,23,28]. Non-income earners, such as students are also noted to be frequent e-bike riders [29]. When it comes to education, many e-bike users possess a college degree or higher [8,21,23,26,28] and have higher educational attainment compared to traditional bicycle users [20]. However, one study found that those without a college degree are more likely to ride e-bikes [27]. In terms of income, some studies indicate a prevalence among low-income individuals [21,27], while others report a higher concentration of middle-class and upper-middle-class users [22,23,26,28]. Notably, e-bike users generally exhibit higher household income levels compared to non-users [8].

Lastly, in terms of family size, E-bike usage is associated with smaller family sizes, particularly among families with one to two members [8]. The average family size of e-bike users is often reported as around 3.7 people, including both working adults and children [21].

2.3. Perceived Advantages of E-Bikes

Several studies have analyzed the perceived advantages of e-bikes in terms of ease of use, convenience, safety, save cost, and environmentally friendly. Ease of use is a key factor driving e-bike adoption, e-bikes significantly reduce physical effort, making them a preferred option over traditional bicycles [23]. The electric assist allows users to travel longer distances with less exertion, which is particularly appealing for commuting and daily transportation needs [28,33]. Some studies, however, suggest that the reduction in physical activity might negatively impact health due to the diminished physical exertion required [34]. Convenience also plays a critical role in the widespread use of e-bikes. Time savings and high accessibility are key factors driving the transition from other modes of transportation to e-bikes [23,34]. Faster speeds, compared to walking or traditional cycling, are cited as positive factors contributing to the popularity of e-bikes [35]. Due to these advantages, e-bikes are primarily used for commuting [6,27], and their perceived utility helps reduce traffic congestion and improve travel efficiency [28]. Safety is another significant factor for e-bike users. Users often feel safer on e-bikes compared to other forms of transportation, particularly in terms of avoiding traffic congestion on major roads [28,34]. However, concerns persist regarding accidents at intersections, poor lighting, and adverse weather conditions [22,30]. Recent technological advancements, such as real-time camera systems, have the potential to enhance safety and further encourage e-bike usage [1]. Cost savings is an essential factor influencing the willingness to adopt e-bikes. The low operational and purchasing costs of e-bikes make them an attractive and affordable transportation option. Cost savings have been consistently cited as one of the most critical factors

influencing the decision to adopt e-bikes [1]. The ability to reduce commuting expenses [23], particularly in comparison to private vehicles, positions e-bikes as a cost-effective alternative.

Lastly, environmental concerns have increasingly become a focus for e-bike users. E-bike users widely recognize their role in reducing environmental impacts, they help mitigate climate change and make e-bikes a more eco-friendly and convenient option [23,28]. E-bike adoption also leads to significant fuel savings and emission reductions, promoting sustainable transportation choices [33,34]. Additionally, as awareness of environmental issues rises, especially among higher-income groups, e-bikes are increasingly seen as a practical way to protect the environment [26].

2.4. Neighborhood Environment Attributes

Multiple studies have examined how neighborhood environment characteristics influence electric bicycle usage, with particular attention to infrastructure and accessibility to subway stations. The availability of adequate cycling infrastructure significantly influences e-bike adoption. Factors such as route coverage, proximity to bike lanes, and station capacity all play crucial roles in encouraging e-bike usage [29,30,33]. A lack of charging points near workplaces and residential areas is noted as a major infrastructure gap, further hindering e-bike adoption [22]. In contrast, rural areas with poor urban cycling infrastructure have seen higher e-bike use due to the absence of dedicated bike lanes [27]. Road density and access to public services are positively correlated with e-bike travel [14]. Accessibility to subway stations also impacts e-bike usage. E-bikes are often used as a first- and last-mile solution for accessing subway stations, with proximity to transport hubs positively influencing the frequency of e-bike trips [20,33]. More connected transport systems, however, are associated with lower household e-bike ownership, indicating that seamless public transport may reduce the need for personal e-bikes [35].

2.5. Vehicle Ownership Characteristics

Vehicle ownership characteristics, especially car ownership, play a complex role in shaping e-bike usage. While one might assume that car owners are less likely to adopt e-bikes due to the convenience of motorized transport, studies show that this relationship is more nuanced. Those who own cars are more likely to use e-bikes for specific types of trips, car owners may still opt to ride e-bikes [8], especially for shorter trips where the e-bike's flexibility and ease of use offer advantages over driving. However, for longer-distance travel or trips to more remote destinations, the likelihood of choosing a car remains higher. Some studies highlight that car ownership continues to influence the choice of travel mode for trips involving longer distances or multiple destinations, where cars are still seen as the more practical option [6].

3. Methods and Data

3.1. Explanatory Variables

This study scrutinizes an array of explanatory variables that may influence e-bike utilization, categorized into four principal groups: socio-demographic characteristics, perceived advantages of e-bikes, neighborhood environmental attributes, and vehicle ownership characteristics. Participants are delineated into two distinct classifications based on their frequency of e-bike usage: e-bike users, defined as individuals who engage with an e-bike four or more times per week, and non-users, characterized as those who utilize e-bikes less frequently.

The analysis encompasses various explanatory variables recognized to impact e-bike adoption. Key socio-demographic factors include gender, age, education, occupation, income, and family size, all of which significantly affect individual transportation preferences. Moreover, the study integrates perceptual variables related to e-bike usage, such as ease of use, convenience, safety, cost efficiency, and environmental sustainability, which reflect respondents' attitudes toward the merits of e-bikes. Furthermore, the investigation delves into infrastructure-related factors, emphasizing the availability of dedicated e-bike lanes and charging stations, as well as the proximity of these amenities to users. The analysis also contemplates car ownership and accessibility to public transportation, particularly

subway stations, to account for alternative mobility options that may curtail e-bike adoption. The anticipated signs of the coefficients are guided by theoretical postulations, with most factors posited to exert a positive influence on e-bike usage, except for car ownership and subway accessibility, which are expected to yield a negative impact on the propensity to adopt e-bikes.

3.2. Data and Sampling Technique

The analysis in this study is based on primary data collected through an online survey conducted in April 2023. The use of online surveys allowed for efficient data collection and processing. Additionally, a convenience sampling method was employed due to its affordability, speed, and ease of application in online environments [36]. The survey consisted of three main sections. The first section, 'Respondent's Profile' focused on analyzing the socio-demographic characteristics of e-bike users and the influence of vehicle ownership characteristics, including the effects of fuel and electric car ownership on e-bike usage. The second section, 'Usage of e-bike and the neighborhood/workplace environment' examined the influence of neighborhood environment attributes on e-bike usage. Specific infrastructure factors such as parking availability, charging stations, dedicated lanes, and road conditions near the respondents' homes or workplaces were analyzed in detail. The third section, 'The Perceived Advantages of E-bikes' required respondents to rate their agreement with various statements using a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The statements covered topics such as ease of use, convenience, safety, cost savings, and environmental impact.

The questionnaire was developed using Questionnaire Star and distributed via social media platforms including WeChat, Weibo, and Little Red Book, targeting relevant groups in Henan Province. A total of 449 responses were collected. To ensure the validity of the data, two screening questions regarding residency and age were included, restricting the sample to individuals aged 16 and above residing in Henan Province. After excluding 46 responses that did not meet these criteria, 403 responses were retained for analysis.

3.3. Econometric Analysis

3.3.1. The Specification of Empirical Model and Its Estimation

The logit model is often used to model an individual's decision to use an e-bike [23,30,31]. Therefore, this study also adopted a logit model to identify factors that affect an individual's decision to use an e-bike. In the empirical model, the dependent variable is a binary variable that would take the value of one if the respondent reported using an e-bike within the last three months, and zero otherwise. The general specification of the logit model is expressed as follows:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_i X_i + \mu_i \quad (1)$$

where, P_i = the probability of using an e-bike, $(1-P_i)$ = the probability of not using an e-bike, X_i = the explanatory variables that affect the likelihood of using an e-bike, β_i = the coefficients for the explanatory variables, $\ln\left(\frac{P_i}{1-P_i}\right)$ represents the log of odds of the probability of using an e-bike to the probability of not using an e-bike.

3.3.2. Likelihood-Ratio Test

The Likelihood-Ratio (LR) test is employed to evaluate the comparative goodness-of-fit between two competing models: the null model and the alternative model [37]. Specifically, the test assesses whether the inclusion of additional predictors significantly improves the model's fit. The null hypothesis (H_0) posits that all coefficients are equal to zero ($\beta_1 = \beta_2 = \dots = \beta_i = 0$), suggesting that none of the explanatory variables have a significant effect on the outcome. Conversely, the alternative hypothesis (H_1) asserts that at least one of the coefficients is not equal to zero ($\beta_1 \neq \beta_2 \neq \dots \neq \beta_i \neq 0$), indicating that the inclusion of one or more variables provides a statistically significant improvement in the model's fit. This test is particularly relevant for examining the factors influencing e-bike usage, as it allows for the evaluation of whether key socio-demographic characteristics, perceived

advantages of e-bikes, neighborhood environment attributes, and vehicle ownership characteristics contribute meaningfully to the likelihood of adopting e-bikes. By comparing the log-likelihoods of the null and alternative models, the LR test helps determine whether the model incorporating these variables offers a better explanation of e-bike usage behavior.

3.3.3. Expectation-Prediction Evaluation

The estimated model is evaluated for accuracy in correctly classifying its observations [38]. The correct classification was obtained when the predicted probability is less than or equal to the cut-off and the observed outcome is 'non-e-bike users' (coded as 0), or when the predicted probability is higher than the cut-off and the observed outcome is 'frequent e-bike users' (coded as 1).

3.3.4. Hosmer-Lemeshow Goodness-Of-Fit Test

The Hosmer-Lemeshow test represents a vital statistical method for evaluating the goodness of fit of logistic regression models [39], with significant applicability in the study of e-bike usage [40,41]. This test examines the alignment between observed event rates and expected event rates across various subgroups within the model population. The null hypothesis (H0) posits that the model adequately fits the data at an acceptable level, while the alternative hypothesis (H1) contends that the model does not precisely fit the data. By applying this test, researchers can ascertain the robustness of their logistic regression model, ensuring that it effectively captures the dynamics influencing e-bike adoption and usage patterns.

4. Results and Analysis

4.1. Respondent Profile and Descriptive Analysis

The demographic profile of the respondents is detailed in Table 2, which provides an overview of the key socio-demographic characteristics of the 403 participants in this study. The sample is composed of 46.15% male and 53.85% female respondents. Among e-bike users, the gender distribution is relatively balanced, with males comprising 48.17% and females 51.83%, suggesting no significant gender disparity in e-bike adoption. In terms of age distribution, the largest proportion of respondents falls within the 30–39 age group (45.66%), followed by those aged 16–29 (40.69%), while only 13.65% are 40 years or older. Family size data reveals that the majority of respondents (61.04%) reside in households consisting of three to four members, while smaller households (1-2 members) account for 15.63%, and larger households (5 or more) make up 23.33%. Occupation is another significant variable, with most respondents (59.06%) working in office jobs, followed by workmen (23.08%) and students (17.87%). Educational attainment shows that nearly half of the respondents (49.38%) have a level of education below college, 29.28% hold a college degree, and 21.34% possess a bachelor's degree or higher. Personal monthly income is fairly evenly distributed, with 34.74% earning less than RMB 2,500, 34.99% earning between RMB 2,500 and RMB 5,000, and 30.27% earning RMB 5,000 or more.

The descriptive analysis further identifies significant variations between e-bike users and non-users. Males represent a slightly higher proportion of e-bike users (48.17%), though the overall gender distribution among users and non-users remains balanced. Age-wise, the largest share of e-bike users is concentrated in the 30–39 age group (45.03%), followed by those aged 16–29 (40.31%), indicating that younger and middle-aged individuals are more likely to adopt e-bikes. Household size also appears to influence e-bike usage, with smaller households (1-2 members) showing a higher percentage of users (18.32%) compared to non-users (13.21%). Notably, occupation and education show distinct trends: office workers and those with a college-level education or higher are more likely to use e-bikes, suggesting that higher education and professional employment may facilitate e-bike adoption. Interestingly, income distribution reveals little variation between users and non-users, indicating that personal income may not be a significant barrier to e-bike usage within the surveyed population.

Table 2. Descriptive Statistics of the Variables.

Variable		Total (n=403)	%	Users Frequenc y	%	No-users Frequenc y	%
Gender	Male	186	46.15 %	92	48.17 %	94	44.34 %
	Female	217	53.85 %	99	51.83 %	118	55.66 %
Age	16-29 years old	164	40.69 %	77	40.31 %	87	41.04 %
	30-39 years old	184	45.66 %	86	45.03 %	98	46.22 %
	40 years old and above	55	13.65 %	28	14.66 %	27	12.74 %
Family size	1-2	63	15.63 %	35	18.33 %	28	13.21 %
	3-4	246	61.04 %	108	56.54 %	138	65.09 %
	5 and above	94	23.33 %	48	25.13 %	46	21.70 %
Occupatio n	Office worker	238	59.06 %	108	56.54 %	130	61.32 %
	Workman	93	23.08 %	53	27.75 %	40	18.87 %
	Student	72	17.86 %	30	15.71 %	42	19.81 %
Education	Below college level	199	49.38 %	87	45.55 %	112	52.83 %
	College education	118	29.28 %	65	34.03 %	53	25.00 %
	Bachelor's degree or higher	86	21.34 %	39	20.42 %	47	22.17 %
Personal monthly income	Less than RMB 2500	140	34.74 %	63	32.98 %	77	36.32 %
	RMB 2500-5000	141	34.99 %	70	36.65 %	71	33.49 %
	RMB 5000 and more	122	30.27 %	58	30.37 %	64	30.19 %

4.2. Econometric Analysis

The results of the binary logistic regression are presented in Table 3. In this regression model, variables are grouped into distinct categories to explain the factors influencing e-bike usage. The first category encompasses socio-demographic characteristics such as gender, age, occupation, education, income, and family size. The second category focuses on the perceived advantages of e-bikes, which include ease of use, convenience, safety, cost savings, and environmental friendliness. The third category examines neighborhood environmental attributes, such as infrastructure for e-bikes and accessibility to subway stations. Lastly, the fourth category addresses vehicle ownership characteristics, covering gas car ownership, electric car ownership, and e-bike ownership. For the sake of brevity, only the significant variables are discussed in detail in this section.

Among the socio-demographic characteristics, family size and occupation emerge as key determinants. Specifically, individuals from medium households (3–4 members) are significantly less likely to use e-bikes, as indicated by the negative and significant coefficient (-0.703, $p < 0.05$). Occupation plays a crucial role, with workmen being more inclined to adopt e-bikes compared to office workers (0.654, $p < 0.05$). Educational attainment also positively affects e-bike usage, as respondents with a college education exhibit a higher likelihood of e-bike adoption (0.541, $p < 0.1$), while those with higher degrees do not show a statistically significant difference.

Regarding perceived advantages, cost savings is the strongest motivator for e-bike use, with a highly significant positive coefficient (1.155, $p < 0.01$), suggesting that individuals who prioritize financial benefits are more likely to adopt e-bikes. However, environmental friendliness has a counterintuitive negative impact (-0.665, $p < 0.1$), indicating that environmental concerns may not be a primary driver in this context.

Infrastructure-related variables significantly influence e-bike adoption as well. The availability of charging stations demonstrates a strong positive effect (0.881, $p < 0.01$), reinforcing the importance of supportive infrastructure in facilitating e-bike usage. Similarly, dedicated e-bike lanes (0.497, $p < 0.1$) positively affect e-bike adoption, underlining the role of safe and accessible cycling infrastructure. However, accessibility to subway stations shows a negative but insignificant relationship with e-bike usage (-0.382), aligning with the expectation that access to alternative modes of public transport may reduce the likelihood of e-bike adoption.

E-bike ownership is a highly significant predictor of e-bike usage (1.027, $p < 0.01$), suggesting that once individuals have access to e-bikes, they are more likely to use them regularly. Conversely, gas car ownership exerts a negative but insignificant effect (-0.264), indicating a potential, though not decisive, deterrent to e-bike adoption.

Table 3. Estimation results of binary logistic regression.

Category	Variables/Reference Variable	Variable Description	Coefficients
Socio-demographic characteristics	Gender	Male	-0.0995
	(Ref. = Female)		
	Age	30-39 years old	0.0526
	(Ref. = 16-29 years old)	40 years old and above	0.292
	Family size	3-4	-0.703**
	(Ref. = 1-2)	5 and above	-0.240
	Occupation	Workman	0.654**
	(Ref. = Office worker)	Student	-0.0864
	Education	College education	0.541*
	(Ref. = Below college level)	Bachelor’s degree or higher	0.290
	Personal monthly income	RMB 2500-5000	0.0717
	(Ref. = Less than RMB 2500)	RMB 5000 and more	-0.107
		Ease of use	-0.0749

Perceived advantages of e-bikes	Convenience		-0.304
	Safety		-0.191
	Save cost		1.155***
	Environmentally friendly		-0.665*
Neighborhoods environment attributes	Infrastructure for e-bike	Parking areas for e-bikes	0.188
		Charging stations	0.881***
		E-bike lanes	0.497*
		Condition of the road	0.270
	Public transportation	Accessibility to subway stations	-0.382
Vehicle ownership characteristics	Gas car ownership		-0.264
	Electric car ownership		0.336
	E-bike ownership		1.027***

* p < 0.1; ** p < 0.05; *** p < 0.01.

Table 4 presents the results of the Likelihood-Ratio (LR) test, which reveals a statistically significant chi-square value ($\chi^2(25) = 87.84$, $p < 0.0000$). This finding leads to the rejection of the null hypothesis, confirming that the inclusion of a range of predictors—including socio-demographic characteristics, perceived benefits of e-bikes, neighborhood attributes, and vehicle ownership—significantly enhances the likelihood of e-bike adoption. These results underscore the essential role that these factors play in shaping e-bike usage behavior. In the Expectation-Prediction Evaluation, the model achieved a correct classification rate of 68.73%, indicating a satisfactory level of accuracy in predicting e-bike usage. However, the moderate sensitivity (64.92%) and specificity (72.17%) highlight the potential for further refinement of the model to enhance its predictive capabilities. The model's fit was further evaluated using the Hosmer-Lemeshow test, where the null hypothesis (H_0) posits that the model adequately represents the data, while the alternative hypothesis (H_1) suggests otherwise. The Hosmer-Lemeshow chi-square statistic was $\chi^2(8) = 10.99$, resulting in a p-value of 0.2025, which exceeds the conventional significance threshold of 0.05. This outcome supports the null hypothesis, indicating that the model fits the data adequately.

Table 4. Model Evaluation and Testing Results.

Test	Statistic	Value	Conclusion
Likelihood-Ratio (LR) Test	Chi-Square (χ^2)	87.84	Reject null hypothesis; predictors significantly enhance the likelihood of e-bike adoption.
	Degrees of Freedom	25	
	p-value	< 0.0000	
Expectation-Prediction Evaluation	Correct Classification Rate	68.73%	Moderate sensitivity and specificity indicate potential for model refinement.
	Sensitivity	64.92%	
	Specificity	72.17%	
Hosmer-Lemeshow Test	Chi-Square (χ^2)	10.99	Support null hypothesis; model adequately fits the data.
	Degrees of Freedom	8	
	p-value	0.2025	

5. Conclusions

This study contributes to the growing body of literature on sustainable transportation by examining the key factors influencing e-bike adoption, with a focus on socio-demographic characteristics, perceived advantages, neighborhood environmental attributes, and vehicle ownership. Utilizing data from an online survey, the research employed a binary logistic regression model to conduct an empirical analysis of E-bike usage behavior, the findings provide several critical insights into the dynamics shaping e-bike usage, offering implications for both policymakers and urban planners aiming to promote more environmentally friendly and cost-effective modes of transportation.

First and foremost, socio-demographic variables, particularly family size and occupation, were found to play a significant role in e-bike adoption. Individuals from medium-sized households (3-4 members) were notably less likely to use e-bikes, perhaps due to logistical constraints or alternative transportation needs within such families. Interestingly, workmen demonstrated a higher propensity to adopt e-bikes compared to office workers, possibly due to the greater flexibility and practicality that e-bikes offer for short- to medium-distance commuting in jobs requiring mobility [42]. Educational attainment was also an important determinant, with respondents holding college-level education exhibiting a higher likelihood of adopting e-bikes, pointing to the role of awareness and knowledge in fostering sustainable transportation choices [43]. These findings suggest that targeted campaigns promoting e-bikes could benefit from focusing on specific occupational groups and educational segments to maximize their impact.

The perceived advantages of e-bikes also significantly influenced usage patterns. Cost savings emerged as the strongest motivator, highlighting that financial considerations are a primary driver for e-bike adoption. This aligns with previous research suggesting that affordability and economic efficiency are key factors in the adoption of sustainable transportation modes, particularly in developing regions [44]. However, contrary to expectations, environmental concerns had a negative effect on e-bike usage. This finding suggests that while e-bikes are generally viewed as environmentally friendly, their adoption is not necessarily driven by eco-conscious motives, but rather by practical and financial benefits. This indicates a potential gap in the public's understanding of the environmental benefits of e-bikes, which could be addressed through more targeted awareness campaigns emphasizing their role in reducing carbon emissions and alleviating urban congestion.

Infrastructure-related factors further reinforced the importance of a supportive environment in facilitating e-bike usage. The availability of charging stations and dedicated e-bike lanes positively influenced e-bike adoption, underscoring the critical role that accessible and well-maintained infrastructure plays in promoting sustainable transportation. Urban planners should prioritize the development of such facilities to encourage greater e-bike use, particularly in densely populated urban areas where congestion and limited parking spaces present significant barriers to car ownership [45]. The insignificant relationship between subway station accessibility and e-bike usage suggests that e-bikes and public transportation may serve complementary roles rather than competing ones, particularly in suburban areas where public transportation options may be limited. Therefore, enhancing the integration between e-bike networks and public transport could further improve urban mobility and reduce reliance on private cars [46].

Vehicle ownership characteristics, particularly e-bike ownership itself, proved to be a significant predictor of e-bike usage. This is consistent with the notion that once individuals invest in e-bikes, their likelihood of regularly using them increases. Conversely, gas car ownership had a negative, though statistically insignificant, impact on e-bike usage, suggesting that while car owners may perceive e-bikes as less attractive, they are not entirely dissuaded from adopting this mode of transportation. This finding is crucial for policymakers aiming to shift urban mobility patterns away from car dependency. Incentives that lower the barriers to e-bike ownership, such as subsidies, tax reductions, or loan schemes, could be particularly effective in accelerating the transition toward more sustainable transportation systems [47].

In conclusion, the findings of this study suggest that while socio-demographic characteristics and practical advantages like cost savings are key drivers of e-bike adoption, infrastructural improvements and targeted awareness campaigns could further accelerate the shift towards

sustainable transportation. The study also reveals that despite the potential of e-bikes to contribute to environmental sustainability, they are primarily adopted for their financial and practical benefits rather than for eco-conscious reasons. This underscores the need for more comprehensive policies that not only improve the practical aspects of e-bike usage, such as infrastructure, but also foster a greater understanding of their environmental benefits. As urban areas worldwide continue to grapple with challenges related to traffic congestion, air pollution, and rising transportation costs, e-bikes offer a promising solution that can contribute to more sustainable urban mobility systems. Future research could explore the long-term environmental impacts of widespread e-bike adoption, particularly in terms of reducing carbon emissions and alleviating pressure on urban transportation networks. By addressing both practical barriers and informational gaps, policymakers and urban planners can better promote e-bikes as a viable and sustainable transportation option, contributing to broader efforts toward achieving sustainability goals in urban mobility.

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References

1. Yasir, A.; Hu, X.; Ahmad, M.; Alvarado, R.; Anser, M. K.; Işık, C.; Choo, A.; Ausaf, A.; Khan, I. A. Factors Affecting Electric Bike Adoption: Seeking an Energy-Efficient Solution for the Post-COVID Era. *Front. Energy Res.* **2022**, *9*, 817107. <https://doi.org/10.3389/fenrg.2021.817107>.
2. Wu, J.; Wu, T. Sustainability indicators and indices: An overview. *Handb. Sustain. Manag.* **2012**, *1*, 65–86. https://doi.org/10.1142/9789814354820_0004.
3. Yale Center for Environmental Law & Policy. Environmental Performance Index. Available online: <https://epi.yale.edu/measure/2024/EPI> (accessed on 10 October 2024).
4. Yale Center for Environmental Law & Policy. Environmental Performance Index. Available online: <https://epi.yale.edu/measure/2024/AIR> (accessed on 10 October 2024).
5. The Ministry of Ecology and Environment announced the national ambient air quality status in May. Available online: https://www.mee.gov.cn/ywdt/xwfb/202406/t20240625_1080014.shtml (accessed on 10 October 2024).
6. Bigazzi, A.; Wong, K. Electric Bicycle Mode Substitution for Driving, Public Transit, Conventional Cycling, and Walking. *Transp. Res. Part D: Transp. Environ.* **2020**, *85*, 102412. <https://doi.org/10.1016/j.trd.2020.102412>.
7. Kroesen, M. To What Extent Do E-bikes Substitute Travel by Other Modes? Evidence from the Netherlands. *Transp. Res. Part D: Transp. Environ.* **2017**, *53*, 377–387. <https://doi.org/10.1016/j.trd.2017.04.036>.
8. Simsekoglu, Ö.; Klöckner, C. A. The Role of Psychological and Socio-Demographical Factors for Electric Bike Use in Norway. *Int. J. Sustain. Transp.* **2019**, *13*(5), 315–323. <https://doi.org/10.1080/15568318.2018.1466221>.
9. Cherry, C. R.; Weinert, J. X.; Xinmiao, Y. Comparative Environmental Impacts of Electric Bikes in China. *Transp. Res. Part D: Transp. Environ.* **2009**, *14*(5), 281–290. <https://doi.org/10.1016/j.trd.2008.11.003>.
10. Bai, L.; Sze, N. N.; Liu, P.; Guo Haggart, A. Effect of Environmental Awareness on Electric Bicycle Users' Mode Choices. *Transp. Res. Part D: Transp. Environ.* **2020**, *82*, 102320. <https://doi.org/10.1016/j.trd.2020.102320>.
11. Ji, S.; Cherry, C. R.; Bechle, J.; Wu, Y.; Marshall, J. D. Electric Vehicles in China: Emissions and Health Impacts. *Environ. Sci. Technol.* **2012**, *46*(4), 2018–2024. <https://doi.org/10.1021/es202347q>.
12. Fishman, E.; Cherry, C. E-bikes in the Mainstream: Reviewing a Decade of Research. *Transp. Rev.* **2016**, *36*(1), 72–91. <https://doi.org/10.1080/01441647.2015.1069907>.
13. McQueen, M.; MacArthur, J.; Cherry, C. The E-Bike Potential: Estimating Regional E-bike Impacts on Greenhouse Gas Emissions. *Transp. Res. Part D: Transp. Environ.* **2020**, *87*, 102482. <https://doi.org/10.1016/j.trd.2020.102482>.

14. Yu, Y.; Jiang, Y.; Qiu, N.; Guo, H.; Han, X.; Guo, Y. Exploring Built Environment Factors on E-bike Travel Behavior in Urban China: A Case Study of Jinan. *Front. Public Health* **2022**, *10*, 1013421. <https://doi.org/10.3389/fpubh.2022.1013421>.
15. Baptista, P.; Pina, A.; Duarte, G.; Rolim, C.; Pereira, G.; Silva, C.; Farias, T. From On-road Trial Evaluation of Electric and Conventional Bicycles to Comparison with Other Urban Transport Modes: Case Study in the City of Lisbon, Portugal. *Energy Convers. Manag.* **2015**, *92*, 10–18. <https://doi.org/10.1016/j.enconman.2014.12.043>.
16. Elliot, T.; McLaren, S. J.; Sims, R. Potential Environmental Impacts of Electric Bicycles Replacing Other Transport Modes in Wellington, New Zealand. *Sustain. Prod. Consum.* **2018**, *16*, 227–236. <https://doi.org/10.1016/j.spc.2018.08.007>.
17. Kazemzadeh, K.; Ronchi, E. From bike to electric bike level-of-service. *Transport Rev.* **2022**, *42*(1), 6–31. <https://doi.org/10.1080/01441647.2021.1900450>.
18. Weinert, J. X.; Burke, A. F.; Wei, X. Lead-acid and lithium-ion batteries for the Chinese electric bike market and implications on future technology advancement. *J. Power Sources* **2007**, *172*(2), 938–945. <https://doi.org/10.1016/j.jpowsour.2007.05.044>.
19. Yang, C.-J. Launching strategy for electric vehicles: Lessons from China and Taiwan. *Technol. Forecast. Soc. Change* **2010**, *77*(5), 831–834. <https://doi.org/10.1016/j.techfore.2010.01.010>.
20. Cherry, C.; Cervero, R. Use characteristics and mode choice behavior of electric bike users in China. *Transp. Policy* **2007**, *14*(3), 247–257. <https://doi.org/10.1016/j.tranpol.2007.02.005>.
21. Cherry, C. R.; Yang, H.; Jones, L. R.; He, M. Dynamics of electric bike ownership and use in Kunming, China. *Transp. Policy* **2016**, *45*, 127–135. <https://doi.org/10.1016/j.tranpol.2015.09.007>.
22. Astegiano, P.; Tampère, C. M. J.; Beckx, C. A Preliminary Analysis Over the Factors Related with the Possession of an Electric Bike. *Transp. Res. Procedia* **2015**, *10*, 393–402. <https://doi.org/10.1016/j.trpro.2015.09.089>.
23. Lin, X.; Wells, P.; Sovacool, B. K. Benign mobility? Electric bicycles, sustainable transport consumption behaviour and socio-technical transitions in Nanjing, China. *Transp. Res. Part A: Policy Pract.* **2017**, *103*, 223–234. <https://doi.org/10.1016/j.tra.2017.06.014>.
24. Global – Are e-bikes the future of urban mobility? Available online: <https://business.yougov.com/content/44158-global-are-e-bikes-future-urban-mobility> (accessed on 10 October 2024).
25. National Bureau of Statistics. Available online: <https://data.stats.gov.cn/adv.htm?m=advquery&cn=E0103> (accessed on 10 October 2024).
26. Bai, L.; Sze, N. N.; Liu, P.; Guo Haggart, A. Effect of environmental awareness on electric bicycle users' mode choices. *Transp. Res. Part D: Transport Environ.* **2020**, *82*, 102320. <https://doi.org/10.1016/j.trd.2020.102320>.
27. Hu, Y.; Sobhani, A.; Ettema, D. To e-bike or not to e-bike? A study of the impact of the built environment on commute mode choice in small Chinese city. *J. Transport Land Use* **2021**, *14*(1), 479–497. <https://doi.org/10.5198/jtlu.2021.1807>.
28. Li, R.; Krishna Sinniah, G.; Li, X. The Factors Influencing Resident's Intentions on E-Bike Sharing Usage in China. *Sustainability* **2022**, *14*(9), 5013. <https://doi.org/10.3390/su14095013>.
29. Timpabi, A. P.; Osei, K. K.; Adams, C. A. Bicycle ownership and utilization in Tamale Metropolis; influencing factors and impacts to sustainable transport. *Heliyon* **2021**, *7*(6), e07133. <https://doi.org/10.1016/j.heliyon.2021.e07133>.
30. Arsenio, E.; Dias, J. V.; Lopes, S. A.; Pereira, H. I. Assessing the market potential of electric bicycles and ICT for low carbon school travel: A case study in the smart city of Águeda. *Transp. Res. Procedia* **2017**, *26*, 119–130. <https://doi.org/10.1016/j.trpro.2017.07.013>.
31. He, Y.; Song, Z.; Liu, Z.; Sze, N. N. Factors Influencing Electric Bike Share Ridership: Analysis of Park City, Utah. *Transp. Res. Rec. J. Transp. Res. Board* **2019**, *2673*(5), 12–22. <https://doi.org/10.1177/0361198119838981>.
32. Simsekoglu, Ö.; Klöckner, C. A. The role of psychological and socio-demographical factors for electric bike use in Norway. *Int. J. Sustain. Transp.* **2019**, *13*(5), 315–323. <https://doi.org/10.1080/15568318.2018.1466221>.
33. Vlakveld, W. P.; Twisk, D.; Christoph, M.; Boele, M.; Sikkema, R.; Remy, R.; Schwab, A. L. Speed Choice and Mental Workload of Elderly Cyclists on E-bikes in Simple and Complex Traffic Situations: A Field Experiment. *Accid. Anal. Prev.* **2015**, *74*, 97–106. <https://doi.org/10.1016/j.aap.2014.10.018>.
34. Castro, A.; Gaupp-Berghausen, M.; Dons, E.; Standaert, A.; Laeremans, M.; Clark, A.; Anaya-Boig, E.; Cole-Hunter, T.; Avila-Palencia, I.; Rojas-Rueda, D.; Nieuwenhuijsen, M.; Gerike, R.; Panis, L. I.; De Nazelle, A.; Brand, C.; Raser, E.; Kahlmeier, S.; Götschi, T. Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: Insights based on health and transport data from an online survey in seven European cities. *Transp. Res. Interdiscip. Perspect.* **2019**, *1*, 100017. <https://doi.org/10.1016/j.trip.2019.100017>.

35. Zhang, Y.; Li, Y.; Yang, X.; Liu, Q.; Li, C. Built Environment and Household Electric Bike Ownership: Insights from Zhongshan Metropolitan Area, China. *Transp. Res. Rec. J. Transp. Res. Board* **2013**, 2387(1), 102–111. <https://doi.org/10.3141/2387-12>.
36. Stratton, S. J. Population Research: Convenience Sampling Strategies. *Prehospital Disaster Med.* **2021**, 36(4), 373–374. <https://doi.org/10.1017/S1049023X21000649>.
37. West, S. G.; Taylor, A. B.; Wu, W. Model Fit and Model Selection in Structural Equation Modeling. In *Handbook of Structural Equation Modeling*; Hoyle, R. H., Ed.; The Guilford Press: New York, NY, USA, 2012; pp. 209–231.
38. Pearce, J.; Ferrier, S. Evaluating the predictive performance of habitat models developed using logistic regression. *Ecol. Model.* **2000**, 133(3), 225–245. [https://doi.org/10.1016/S0304-3800\(00\)00322-7](https://doi.org/10.1016/S0304-3800(00)00322-7).
39. Archer, K. J.; Lemeshow, S. Goodness-of-fit Test for a Logistic Regression Model Fitted using Survey Sample Data. *Stata J.* **2006**, 6(1), 97–105. <https://doi.org/10.1177/1536867X0600600106>.
40. Cai, J.; Zhao, J.; Liu, J.; Shen, K.; Li, X.; Ye, Y. Exploring Factors Affecting the Yellow-Light Running Behavior of Electric Bike Riders at Urban Intersections in China. *J. Adv. Transp.* **2020**, 2020(1), 1–12. <https://doi.org/10.1155/2020/8573232>.
41. Haufe, S.; Boeck, H. T.; Häckl, S.; Boyen, J.; Kück, M.; Van Rhee, C. C.; Graf Von Der Schulenburg, J.-M.; Zeidler, J.; Schmidt, T.; Johannsen, H.; Holzward, D.; Koch, A.; Tegtbur, U. Impact of electrically assisted bicycles on physical activity and traffic accident risk: A prospective observational study. *BMJ Open Sport Exerc. Med.* **2022**, 8(4), e001275. <https://doi.org/10.1136/bmjsem-2021-001275>.
42. Kohlrautz, D.; Kuhnimhof, T. E-Bike Charging Infrastructure in the Workplace—Should Employers Provide It? *Sustainability* **2023**, 15(13), 10540. <https://doi.org/10.3390/su151310540>.
43. Mosca, O.; Lauriola, M.; Manunza, A.; Lorenzo Mura, A.; Piras, F.; Sottile, E.; Meloni, I.; Fornara, F. Promoting a sustainable behavioral shift in commuting choices: The role of previous intention and “personalized travel plan” feedback. *Transp. Res. Part F.* **2024**, 106, 55–71. <https://doi.org/10.1016/j.trf.2024.06.027>.
44. Shah, K.J.; Pan, S.-Y.; Lee, I.; Kim, H.; You, Z.; Zheng, J.-M.; Chiang, P.-C. Green transportation for sustainability: Review of current barriers, strategies, and innovative technologies. *Front. Clean. Prod.* **2021**, 326, 129392. <https://doi.org/10.1016/j.jclepro.2021.129392>.
45. Parmar, J.; Das, P.; Dave, S. M. Study on demand and characteristics of parking system in urban areas: A review. *J. Traffic Transp. Eng.* **2020**, 7(1), 111–124. <https://doi.org/10.1016/j.jtte.2019.09.003>.
46. Yin, A.; Chen, X.; Behrendt, F.; Morris, A.; Liu, X. How electric bikes reduce car use: A dual-mode ownership perspective. *Transp. Res. Part D* **2024**, 133, 104304. <https://doi.org/10.1016/j.trd.2024.104304>.
47. Leibowicz, B.D. Policy recommendations for a transition to sustainable mobility based on historical diffusion dynamics of transport systems. *Energy Policy* **2018**, 119, 357–366. <https://doi.org/10.1016/j.enpol.2018.04.066>.

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