Numerical Methods in Civil Engineering, 10-1 (2025) 68-81

Numerical Methods in Civil Engineering

Journal Homepage: https://nmce.kntu.ac.ir/

Modeling and Heterogeneity in Shared Electric Vehicles Adoption in Developing Cities

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ARTICLE INFO

RESEARCH PAPER

Article history:
Received:
August 2025
Revised:
October 2025
Accepted:
October 2025

Keywords:
Electric Vehicles,
Shared Electric Vehicles,
Perceived Benefits,
Heterogeneity,
Ecological Awareness.

Abstract:

Electric vehicle technology is key to sustainable development, by reducing air pollution and dependence fossil fuel. However, adoption in developing markets remains slow. Shared electric vehicles help address high initial costs, improving accessibility. This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating perceived benefits, environmental concerns, and hedonic motivations. Perceived benefits play a central role, influenced by performance expectations and social impacts. A total of 303 data points were collected through an online survey and analyzed with structural equation modeling. The results indicated that all seven hypotheses were supported. The findings highlight that performance expectations and social influences significantly shape perceived benefits, while effort expectations, hedonic motivations, facilitating conditions, and environmental concerns drive adoption. Additionally, the study explored the heterogeneity of user's socio-economic variables, such as gender and age, in the acceptance of shared electric vehicles. These insights can inform policymakers and service providers to design effective interventions that encourage SEV use of in developing cities.

1. Introduction

In recent decades, the global transportation sector has experienced significant changes due to technological advances and increased awareness of environmental issues, leading to a shift toward sustainable methods [1]. Electric vehicles have gained considerable attention for their potential to reduce urban air pollution and decrease dependence on fossil fuels [2]. Shared electric vehicle programs have also emerged as an effective urban transportation solution, promoting the efficient use of vehicles and reducing greenhouse gas emissions, thereby contributing to a better urban environment [3].

Tehran, the capital of Iran, suffers from severe traffic congestion and air pollution, largely driven by rapid urbanization and dependence on private cars [4]. The introduction of shared electric vehicle programs in Tehran is expected to tackle these challenges and improve urban transportation. Understanding the factors influencing the adoption and choice of shared electric vehicles in Tehran is crucial for effective policymaking and the development of necessary infrastructure [5]. Few studies have simultaneously analyzed psychological, social and demographic factors in developing cities. This study addresses this gap by modeling SEV adoption in Tehran through an extended UTAUT framework that incorporating perceived benefits, environmental concerns and hedonic motivation.

With Tehran's growing population and urban expansion, the demand for vehicles has increased, leading to more traffic congestion and declining air quality [6]. One proposed solution to these problems is the introduction of shared electric vehicle programs, which could help reduce traffic and reduce air pollution [7]. However, the adoption of these programs by Tehran's residents is challenging due to limited awareness and insufficient infrastructure. Understanding the factors that influence the acceptance and use of shared

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https://doi.org/10.61882/NMCE.2508.1099

electric vehicles such as attitudes, awareness, and demographic factors like age, gender, and income is essential for developing effective policies and improving urban infrastructure [8]. This research aims to identify and analyze these factors and suggest strategies to increase the adoption and use of shared electric vehicles in Tehran.

The main objective of this research is to examine and model the factors influencing the adoption of shared electric vehicles in Tehran and to propose a model for better understanding the behavior of users who utilize these vehicles.

To evaluate the impact of various factors on individuals' attitudes and willingness to use shared electric vehicles, a standard online questionnaire will be utilized. The following hypotheses are proposed in this regard:

Hypothesis 1: It is assumed that all respondents have used a vehicle at least once.

Hypothesis 2: It is assumed that at least half of the respondents have some familiarity with shared vehicle systems.

Shared electric vehicle programs are increasingly recognized as an effective strategy to address urban challenges. In cities like Tehran, such initiatives can reduce traffic congestion and dependence on fossil fuels, while simultaneously improving air quality and mitigating greenhouse gas emissions [9,10,11].These efforts not only help improve the environment and reduce the negative effects of city traffic but also enhance economic performance [12]. Overall, research has shown that shared electric vehicles are a key approach to achieving sustainable urban development and reducing environmental impacts [13].

2. Literature Review

To address transportation challenges such as air pollution, parking space limitations, and traffic congestion, policymakers and service operators have introduced alternatives to gasoline-powered vehicles. These alternatives include improving public transportation performance, implementing incentive policies for purchasing electric vehicles, and introducing shared vehicle systems [14]. Despite government policies aimed at providing benefits to the electric vehicle industry, the use of these vehicles in global markets remains low.

There are several barriers to purchasing electric vehicles that limit their use. These barriers include the higher cost of electric vehicles compared to similar gasoline-powered cars, the high additional cost of battery replacement, the rapid depreciation of electric vehicles, which results in lower resale value, and the limited availability of electric vehicle charging stations [15, 16]. These issues restrict the adoption and particularly the purchase of electric vehicles.

The concept of shared vehicle systems originated in the 1940s with the goal of improving demand, sharing schemes, and expanding technology [17, 18]. Numerous studies have shown that shared vehicle systems, including shared electric vehicles, can lead to a reduction in car ownership [19]. Additionally, users of shared electric vehicles are more likely to consider purchasing electric vehicles in the future [20]. Therefore, shared electric vehicles can familiarize users with this new technology and accelerate the adoption of electric vehicles.

2.1 Theories of Human Behavior

There are several theories in the literature that explain human behavior. The Technology Acceptance Model (TAM), introduced by Fred Davis over 25 years ago, has become a key framework for studying the factors that influence how users accept new technology. TAM suggests that two factors—perceived ease of use and perceived usefulness—play a central role in the complex relationship between system features (external factors) and how likely a system is to be used [21]. Rooted in the psychology-based theories of Reasoned Action (TRA) and Planned Behavior (TPB), TAM has been instrumental in understanding user behavior toward technology. To conduct thorough and systematic research in this field, it's crucial to understand the model's origins, evolution, adaptations, and its limitations [22].

The theory of planned behavior suggests that three main factors independently influence a person's intention to act. First, attitude toward the behavior, which is how positively or negatively someone views the behavior. Second, the subjective norm, or the social pressure a person feels to either engage in or avoid the behavior. Lastly, perceived behavioral control, which refers to how easy or difficult a person believes the behavior will be to perform, based on their past experiences and potential obstacles [23].

The TAM laid the groundwork for the development of the Unified Theory of Acceptance and Use of Technology (UTAUT) that theorizes that four key constructs are crucial as direct determinants of user acceptance and behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. The names of these constructs capture their core ideas and are designed to be applicable across various theoretical perspectives [24].

The Unified Theory of Acceptance and Use of Technology (UTAUT) is regarded as the most comprehensive model for explaining consumer behavior toward new technologies, surpassing earlier models. Recently, UTAUT has been expanded to include additional constructs specific to different contexts and fields of study. For instance, UTAUT2 incorporates factors like hedonic motivation, price value, and habit to better understand technology adoption in varied scenarios [25].

2.2 Adoption of Electric and Shared Electric Vehicles

Shared electric vehicle systems (ECS) introduce two key innovations compared to traditional carbon-fueled private cars. The first innovation is the shift from private to shared car ownership, and the second is the transition from carbon-fueled to electric vehicles. ECS can appeal to a market of individuals who are interested in car sharing and those who are attracted to electric vehicles but uncertain about purchasing them [14].

In 2018, Kai Zheng [26] used the Theory of Planned Behavior and a structural model to provide a deeper understanding of the adoption of shared electric vehicles and strategies for promoting them. The study offered suggestions to increase the use of shared electric vehicles, including making resources like charging facilities and service stations more accessible, creating social spaces like free trials and sharing platforms, and strengthening supportive policies such as financial incentives and legal guarantees. In 2019, Jan Schluter [27] utilized the Technology Acceptance Model to examine the impact of shared vehicle usage on the adoption of electric vehicles. The study analyzed five predictors of electric vehicle adoption: mobility, car ownership, urbanization, environmental awareness, and interest in technology. It found that individuals who had used shared vehicles perceived electric vehicles as more useful than those who hadn't and showed a greater willingness to purchase electric vehicles. In 2019, Vanduy Tran [28] used an extended version of the Unified Theory of Acceptance and Use of Technology to examine structural models of shared electric vehicle adoption in developing countries. The study found that hedonic motivations had a significant impact on people's behavioral intentions to use shared electric vehicles in the future. Additionally, performance expectations, ease of use, and familiarity with the concept of shared vehicles also influenced adoption. However, social influences did not affect the acceptance of shared electric vehicles in this study. In 2021, Jiawei Hu and colleagues [29] explored cost-effective policy tools to increase the adoption of electric vehicles, focusing on shared electric vehicles. Using the Theory of Planned Behavior and a regularized logistic regression model, they examined the factors influencing the adoption of shared electric vehicles. Environmental variables and perceived benefits, including economic and safety advantages, were key factors. The study concluded that government agencies could boost adoption by providing dedicated parking spaces for shared electric vehicles in communities. In 2022, John Silberer and colleagues [30] applied the Unified Theory of Acceptance and Use of Technology to investigate the factors influencing the adoption of shared electric vehicles in less populated areas like villages and small towns. The study found that performance expectations, hedonic motivations, and facilitating conditions were the most important factors in these areas. The study recommended that policymakers assess the technical and economic feasibility of shared electric vehicles before implementing the system. In 2021, Riccardo Curtale and colleagues [14] identified shared electric vehicles (EVs) as a solution to the negative impacts of urban transportation, believing their adoption could be enhanced by integrating autonomous fleets. They studied people's behavioral intentions to use autonomous shared EVs, transitioning from regular shared EVs. Using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) and structural models, they examined this in European countries like France, Spain, Italy, and the Netherlands. The study found that hedonic motivations were stronger predictors than safety concerns, while performance expectations and social influences had lesser indirect effects on the intention to use autonomous shared EVs. In summary, individuals interested in ECS often resemble early adopters in the technology adoption life cycle, typically characterized by being young and well-educated. However, there is a notable lack of empirical research that thoroughly examines the combined effects of psychological factors, socio-demographic aspects, and transportation-related characteristics on this adoption.

3. Conceptual Framework

As previously mentioned, the UTAUT has been more effective than several other theories in explaining behavioral intentions across different contexts. Building on this, we utilize a model derived from UTAUT to analyze individuals' intentions to adopt ECS. This section uses Structural Equation Modeling (SEM) to investigate the influence of psychological and socio-demographic factors on ECS adoption. In addition to the original UTAUT components—performance expectancy, effort expectancy, social influence, and facilitating conditions—our model incorporates three additional factors: perceived benefits, ecological awareness, and hedonic motivation.

Recent studies indicate that perceived benefits play a crucial role in the acceptance of shared electric vehicles, as highlighted in related research. Performance expectancy relates to how individuals perceive the efficiency and practical advantages of technology. When people believe that using electric vehicles will enhance their productivity, this belief translates into perceived benefits, such as cost savings on fuel, reduced maintenance costs, and improved quality of life [31]. Additionally, social influences significantly shape perceived benefits [32]. Observing positive experiences from peers using electric vehicles fosters trust and strengthens perceived advantages, encouraging adoption. Social support and validation from trusted individuals can enhance perceived benefits, leading to increased acceptance of this technology.

Given that performance expectancy and social influences have a direct impact on users' perceived benefits, the following hypotheses can be proposed:

Hypothesis 1. Performance expectancy in using shared electric vehicles positively influences users' perceived benefits.

Hypothesis 2. Social influences that people accept have a positive effect on the perceived benefits of users of shared electric vehicles.

It is anticipated that the use of shared electric vehicles can help reduce traffic congestion [33]. Studies also indicate that as concerns about the safety of electric vehicles decrease, their acceptance increases [34]. Considering government incentive policies, it is assumed that shared electric vehicles could be more cost-effective than private cars. These factors—reducing traffic congestion, enhancing safety, and lowering economic costs—can increase users' perceived benefits. Therefore, we propose the following hypothesis:

Hypothesis 3. Perceived benefits, such as reduced costs, improved safety, and less traffic, positively influence the intention to use shared electric vehicles over private cars.

Facilitating conditions refer to consumers' perceptions of the resources and support available to perform a behavior [25]. Singh and colleagues in 2023 [35] found that infrastructure can aid the acceptance of electric vehicles, influencing users by considering social, economic, and environmental factors. These conditions can help users more easily and effectively utilize shared electric vehicles. Therefore, we propose the following hypothesis:

Hypothesis 4. Facilitating conditions have a positive impact on the behavioral intention to use shared electric vehicles.

Effort expectancy refers to the ease with which consumers believe they can use a technology [25]. It aligns with the concept of perceived ease of use in the Technology Acceptance Model (TAM). Since shared electric vehicles are straightforward and user-friendly, this ease of use can increase the intention to use them. Research has shown that effort expectancy is a crucial factor in the adoption of shared electric vehicles and electric vehicles [36]. Therefore, we propose the following hypothesis:

Hypothesis 5. Effort expectancy positively impacts the intention to use shared electric vehicles.

Hedonic motivation is defined as the enjoyment or pleasure derived from using a technology [25]. The relationship between hedonic motivation and behavioral intention has been demonstrated in numerous studies on technology adoption. These studies measure the extent of pleasure that using shared electric vehicles provides to users. Madigan and colleagues [37] found that the fun and enjoyment of using a transportation method directly influence the intention to use it. Therefore, we propose the following hypothesis:

Hypothesis 6. Hedonic motivation positively impacts the intention to use shared electric vehicles.

Electric vehicles (EVs) can be a strong alternative for reducing greenhouse gas emissions in transportation [11]. They help decrease reliance on fossil fuels by using alternative energy sources, thereby enhancing energy sustainability [38]. EVs offer significant advantages over conventional gasoline vehicles in terms of energy efficiency and pollution reduction. Given the possibility of fuel price deregulation and the severe urban air pollution caused by the daily consumption of 97.1 million liters of gasoline in Iran [39], especially in large cities, we propose the following hypothesis:

Hypothesis 7. Environmental concerns positively influence individuals' intention to use shared electric vehicles.

The proposed research model can be seen in Figure 1.

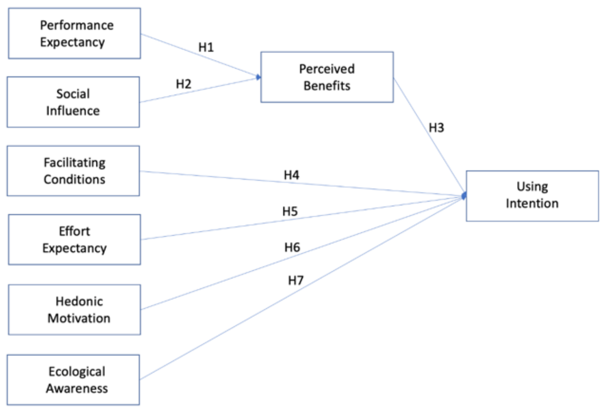

Fig. 1: Conceptual framework of the extended UTAUT model

4. Methodology and Data

4.1 Survey

This study targets the attitudes of potential users toward shared electric vehicles. The survey includes three sections:

1. **Introduction**: This section introduces shared electric vehicles, explaining their electric and shared nature, along with a brief overview of their benefits and uses. It also includes images and a short video.
2. **Main Questionnaire**: Contains 27 statements to measure latent variables, rated on a seven-point Likert scale from "strongly agree" to "strongly disagree"[40]. Table 1 includes all statements along with their mean, and standard deviation.
3. **Demographics**: Gathers demographic information such as age, gender, income, and education level.

The questionnaire was primarily based on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, extended with additional constructs. It consisted of 8 factors, each measured by 3–6 items. Items were adapted from validated prior studies and adjusted to the SEV context in Tehran. Details of each factor and its measurement items are reported in Table 1.

In this study, the final version of the online questionnaire was developed for distribution via Google Docs. Over a period of three months, starting on February 1, 2024, the questionnaire was shared through social media platforms like Twitter and Instagram, messaging apps like WhatsApp and Telegram, email, and in-person distribution using a QR code. To ensure the quality of the data, specific measures were taken in the questionnaire. A question in the second section was included to assess the respondents' experience and familiarity with the vehicles. Individuals who did not have full experience and familiarity with the vehicles were excluded from the analysis. Additionally, in the second section, obvious but unrelated questions were included to assess respondents' attention to the questionnaire. Respondents who gave incorrect answers were excluded from the modeling process. After removing these responses, 303 out of a total of 342 samples were identified as valid data, resulting in a response rate of 88.59%. To enhance the likelihood of adopting shared electric vehicles (SEVs), our primary focus is on individuals under 45 years old who have attained higher education levels (College/Undergraduate, Postgraduate, or higher). These respondents are anticipated to be key decision-makers regarding SEV sharing in the future. Since our surveys are randomly distributed online, they tend to attract younger, highly educated participants who align with the target demographic for this study [29].

The current study employed a Revealed Preference (RP) approach, focusing on participant's stated behavioral intentions toward SEVs. A Stated Preference (SP) design was not included due to the limited familiarity of the public with SEVs in Iran. Future research is encouraged to integrate SP or hybrid SP–RP methods for more robust insights. Means and standard deviations are based on data collected in the current study. Sources for each construct are provided in the last column.

Table 1: Questionnaire items.

Constructs	Items	Mean	Standard Deviation
Environmental Awareness (EA)	1. I use electric vehicles because of the air pollution crisis.	2.62	1.225
	2. Electric vehicles help preserve the environment for the next generation.	1.70	0.89
	3. Using an electric vehicle allows me to exhibit environmentally friendly behavior.	0.87	1.89
Social Influences (SI)	1. Social approaches and trends influence the decision to use electric vehicles.	2.83	1.007
	2. People whose opinions I value think that a shared electric vehicle is better for me than a regular car.	2.81	0.977
	3. I think that shared electric vehicles will become popular in society.	2.16	0.957
Facilitating Conditions (FC)	1. With more charging stations and service centers, I will use shared electric vehicles instead of a personal car.	2.02	0.900
	2. I believe government incentives, such as dedicated parking spaces, will encourage me to use shared electric vehicles instead of a personal car.	1.98	0.929
	3. I believe government incentives, such as dedicated traffic schemes for electric vehicles, will encourage me to use shared electric vehicles instead of a personal car.	1.89	0.89
	4. I believe government incentives, such as exclusive use of special lanes and BRT routes, will encourage me to use shared electric vehicles instead of a personal car.	2.05	1.063
Hedonic Motivations (HM)	1. It is fun to use electric vehicles because of their smoothness and high acceleration.	2.33	0.93
	2. Using a shared electric vehicle service in Tehran is fun.	2.36	0.938
	3. Using a shared hybrid vehicle service in Tehran is fun.	2.48	0.918
	4. Using advanced electric vehicles instead of personal cars for a reasonable cost is enjoyable for me.	1.74	0.755
Perceived Benefits (PB)	1. A shared electric vehicle service is a good alternative to owning a car.	2.42	1.06
	2. A shared electric vehicle service will be safer than personal cars.	1.99	0.867
	3. A shared electric vehicle service can help reduce traffic congestion by reducing car ownership.	2.21	1.006
Performance Expectations (PE)	1. Using electric vehicles enhances my technical learning and activities.	2.70	0.979
	2. I find electric vehicles useful for my travel.	2.41	1.044
	3. I can access other transportation modes, such as the metro, by using shared electric vehicles.	2.19	0.879
Effort Expectations (EE)	1. I believe that electric vehicles can be used without stress.	2.48	1.035

	2. Using an electric vehicle does not require special expertise.	2.43	0.932
	3. I can easily and quickly learn to use shared electric vehicles.	1.88	0.765
Using Intention (UI)	1. I expect to have a clear and understandable interaction with electric vehicles.	1.96	0.72
	2. I expect to have a clear and understandable interaction with shared electric vehicles.	2.12	0.821
	3. If the costs are reasonable, I will buy a hybrid vehicle in the near future.	2.01	0.997
	4. If the costs are reasonable, I will buy an electric vehicle in the near future.	2.05	1.031

5. Methodology

The structural equation modeling (SEM) technique has been employed as the primary method for modeling in this research. Specifically, the study utilized the Covariance-Based Structural Equation Modeling (CB-SEM) approach, a covariance-based method used in SEM [41]. The proposed model comprises 7 latent variables, 27 observed variables, and 7 relationships. Given the model's complexity, the AMOS software was chosen for its comprehensive capabilities, fewer limitations, and higher speed and accuracy. A two-step approach was applied, with the measurement model assessed first, followed by the structural model evaluation in AMOS.

In the **measurement model** of CB-SEM, the equations describe the relationship between latent variables and their observed indicators:

$$y_j=\lambda_{ij}\eta_i+\epsilon_j$$

Here, y_j represents the observed indicator, λ_{ij} is the factor loading of indicator j on latent variable η_i, and ϵ_j is the measurement error associated with y_j [42].

In the **structural model**, the equations represent the causal relationships among latent variables:

$$\eta_i=\sum_{j=1}^{m}\beta_{ij}\,\eta_j+\sum_{k=1}^{n}\gamma_{ik}\xi_k+\zeta_i$$

In this equation, η_i is the endogenous latent variable, β_{ij} are the regression coefficients representing the influence of other endogenous latent variables η_j on η_i, ξ_k are exogenous latent variables, γ_{ik} are the path coefficients from ξ_k to η_j, and ζ_i denotes the disturbance term or residual error for η_i [42, 43].

In the structural equation model, **Perceived Benefits** (η_3) is influenced by **Performance Expectancy** (ξ_1)and **Social Influence** (ξ_2), represented by the equation

$$\eta_3=\gamma_{31}\xi_1+\gamma_{32}\xi_2+\zeta_3$$

, where γ_{31} and γ_{32} are the path coefficients. Additionally, **Using Intention** (η_6) is influenced by **Effort Expectancy** (η_1), **Facilitating Conditions** (η_2) , **Perceived Benefits** (η_3) , **Hedonic Motivation** (η_4) , and **Ecological Awareness** (η_5) , expressed by the equation

$$\eta_6=\beta_{61}\eta_1+\beta_{62}\,\eta_2+\beta_{63}\,\eta_3+\beta_{64}\,\eta_4+\beta_{65}\,\eta_5+\zeta_6$$

, where β_{61} to β_{65} represent the respective path coefficients. These equations illustrate the causal relationships among the latent variables within the CB-SEM framework.

6. Results and Discussion

In the full sample of 303 participants, 148 respondents were female, and 155 were male (Table 2). As anticipated, the majority of respondents were young to middle-aged adults with a high level of education [29]. The largest age group, comprising 53.13% of the sample, was between 25 and 44 years old, which aligns with the primary demographic for car usage and purchasing. Additionally, most respondents were well-educated. This study employed non-probability online sampling, restricted to respondents under 45 years old with higher education. While this group represents early adopters and potential decision-makers for SEVs, it limits the generalizability of the findings to the broader population of Tehran. This limitation is acknowledged to ensure cautious interpretation of the results.

Table 2: Description of sample structure characteristic.

Description	Type	Obs.	Percentage (%)
Gender	Male	155	51.15%
	Female	148	48.85%
Age	15 to 24	92	30.36%
	25 to 44	161	53.13%
	45 to 64	38	12.54%
	Over 65	12	3.96%
Educational Level	High school or less	1	0.33%
	Diploma	51	16.83%
	Bachelor's Degree	113	37.29%
	Master's Degree	105	34.65%
	Doctorate	31	10.23%
	Postdoctoral Degree	2	0.66%
Income Level	0 to 10 million Toman	170	56.1%
	10 to 30 million Toman	97	32.01%
	30 to 70 million Toman	28	9.24%
	Over 70 million Toman	8	2.64%
Marital Status	Single	226	74.58%
	Married	77	25.41%
Number of Cars in Family	0	6	1.98%
	1	108	35.64%
	2 or more	189	62.37%
Driver's License	Yes	282	93.06%
	No	21	6.93%

While individuals aged 15 cannot legally drive, they are included here as potential future users of SEVs.

6.1 Validity and reliability of analysis

In this study, Excel software was used for data sorting, calculating the standard deviation for each sample, and preparing the data for entry into SPSS software. The SPSS software is a comprehensive statistical tool used for data analysis. This software is capable of importing collected data, providing descriptive statistics, sorting data, calculating Cronbach's alpha to assess the reliability of questionnaires designed with a Likert scale, conducting exploratory factor analysis, and performing other analyses. In this study, AMOS software was used for data modeling. Since the theoretical hypotheses were examined in this study, this software was employed. The measurement model, as mentioned, illustrates the relationship between latent variables and their associated observed variables [44]. In Table 3, the results obtained from the measurement model are clearly presented. As shown, all factor loadings, except for the first factor loading of the ecological awareness and the fourth factor loading of the hedonic motivation variable, are significantly greater than the recommended value of 0.6 [45]. The fourth factor loading of the hedonic motivation variable and the first factor loading of the ecological awareness variable are greater than 0.5. Although a few items showed factor loadings between 0.5 and 0.6, they were retained because they met the minimum threshold reported in prior SEM research [46], and removing them did not improve the model fit. Additionally, some items reported very low mean values (close to 1 on a 7-point scale). These values may indicate response bias or unfamiliarity with SEVs among certain respondents. This limitation should be considered when interpreting the results. The Cronbach's alpha for the latent variables of social influence, hedonic motivation, facilitating conditions, and usage intention is greater than 0.7 [47], and for the latent variables of ecological awareness, performance expectancy, perceived benefits, and effort expectancy, the Cronbach's alpha is greater than 0.6 **[48].**

Table 3: Factor loadings and Cronbach’s Alpha of the constructs.

Constructs	Item	Factor Loading	Cronbach's Alpha
Ecological Awareness (EA)	1	0.534	0.642
	2	0.786	
	3	0.835	
Social Influences (SI)	1	0.788	0.701
	2	0.661	
	3	0.675	
Facilitating Conditions (FC)	1	0.716	0.791
	2	0.765	
	3	0.847	
	4	0.625	
Hedonic Motivations (HM)	1	0.705	0.743
	2	0.849	
	3	0.691	
	4	0.580	
Perceived Benefits (PB)	1	0.788	0.629
	2	0.626	
	3	0.737	
Performance Expectancy (PE)	1	0.743	0.636
	2	0.710	
	3	0.720	
Effort Expectancy (EE)	1	0.717	0.660
	2	0.649	
	3	0.782	
Using Intention (UI)	1	0.786	0.747
	2	0.723	
	3	0.687	
	4	0.663	

6.2 Results of the SEM model:

In this study, a structural model was presented to examine the relationships between the latent variables. The results of the structural model are provided in Table 4. This table shows that all relationships between the latent variables have a t-value greater than 1.96 (equivalent to a p-value less than 5%), except for perceived benefits, which has a t-value greater than 1.645 (equivalent to a p-value less than 0.1). A significance level of 0.1 was adopted in addition to the conventional 0.05. This approach has been used in behavioral and social science studies with relatively small or heterogeneous samples, where a more flexible threshold helps to capture marginally significant effects that may still have theoretical importance. Therefore, the first seven relationships proposed in this study have been confirmed.

H1: Performance Expectancy (PE) significantly influences Perceived Benefits (PB) ($\beta = 0.686$, $p < 0.001$), demonstrating that users’ expectations about performance shape their perception of SEV benefits.

H2: Social Influence (SI) significantly affects Perceived Benefits (PB) ($\beta = 0.561$, $p = 0.005$), implying that social pressure enhances the perception of SEV advantages.

H3: Perceived Benefits (PB) positively influence Using Intention (UI) ($\beta = 0.111$, $p = 0.096$), showing that individuals perceiving higher benefits are more likely to intend to use SEVs.

H4: Facilitating Conditions (FC) positively influence Using Intention (UI) ($\beta = 0.131$, $p = 0.046$), showing that supportive infrastructure and available resources encourage SEV usage.

H5: Effort Expectancy (EE) has a strong and significant effect on Using Intention (UI) ($\beta = 0.416$, $p < 0.001$), indicating that perceived ease of use strongly drives adoption intention.

H6: Hedonic Motivation (HM) significantly affects Using Intention (UI) ($\beta = 0.185$, $p = 0.008$). This suggests that individuals who enjoy the use of SEVs are more willing to adopt them.

H7: Ecological Awareness (EA) has a significant positive effect on Using Intention (UI) (β = 0.126, p = 0.05), indicating that greater ecological awareness increases the likelihood of adopting shared electric vehicles.

From the perspective of users regarding the adoption of shared electric vehicles, variables such as ecological awareness, perceived benefits, facilitating conditions, effort expectancy, and hedonic motivations have a positive impact on users' intention to use shared electric vehicles. Among these variables, effort expectancy has the greatest influence on the intention to use shared electric vehicles. According to the proposed hypotheses, the variables of ecological awareness, facilitating conditions, perceived benefits, effort expectancy, and hedonic motivations have a positive impact on users' intention to use shared electric vehicles. Additionally, according to the proposed hypotheses, the variables of performance expectancy and social influence positively affect the perceived benefits variable. All these hypotheses have been confirmed, with p-values less than 0.1 [29]. In examining users' behavioral perspectives toward shared electric vehicles, performance expectancy and social influence positively impact users' perceived benefits. Among these variables, performance expectancy has the greatest influence on perceived benefits.

Various studies have demonstrated the positive impact of ecological awareness [49, 50], effort expectancy [28, 51], facilitating conditions [52, 53], perceived benefits [29, 54, 55], and hedonic motivations [56, 57] on the adoption of shared electric vehicles, which aligns with the findings of this study.

Table 4: Structural equation modeling (SEM) results (structural model).

Hypothesis	Path	Coefficient	Standard Error	P-Value	Result
1	EA → UI	0.126	0.064	0.05	Supported
2	HM → UI	0.185	0.070	0.008	Supported
3	FC → UI	0.131	0.066	0.046	Supported
4	EE → UI	0.416	0.090	0.000	Supported
5	PE → PB	0.686	0.206	0.000	Supported
6	SI → PB	0.561	0.200	0.005	Supported
7	PB → UI	0.111	0.066	0.096	Supported

Examining the heterogeneity of socioeconomic variables:

In this study, to examine the heterogeneity of socioeconomic variables regarding the use of shared electric vehicles, variables such as gender and age were analyzed for heterogeneity.

The results of this study show significant differences between genders in the model of shared electric vehicle adoption. For men, performance expectancy significantly impacts perceived benefits, indicating that when men have high performance expectations of electric vehicles, they perceive greater benefits. Additionally, social influence significantly affects perceived benefits, highlighting the importance of others' opinions and behaviors in men's decision-making. Ecological awareness also has a positive and significant impact on men's intention to use, showing that the more men are aware of the environmental benefits of electric vehicles, the more likely they are to use them. Hedonic motivations also significantly influence usage intention, indicating the importance of personal enjoyment and satisfaction in men's decision-making. These findings are presented in Table 5.

Table 5: Structural equation modeling (SEM) results (structural model) for men.

Hypothesis	Path	Coefficient	Standard Error	P-Value	Result
1	EA → UI	0.153	0.072	0.034	Supported
2	HM → UI	0.381	0.118	0.001	Supported
3	FC → UI	0.055	0.072	0.450	Not Supported
4	EE → UI	0.265	0.101	0.009	Supported
5	PE → PB	0.561	0.274	0.041	Supported
6	SI → PB	0.884	0.313	0.005	Supported
7	PB → UI	0.090	0.083	0.278	Not Supported

For women, different results are observed. Performance expectancy has a much stronger relationship with perceived benefits, indicating a stronger influence of this variable for women compared to men. Social influence also significantly impacts perceived benefits for women, similar to men, highlighting the importance of social opinions in women's decision-making. However, ecological awareness does not significantly impact women's intention to use, which may reflect a difference in how this issue is valued between the two genders. Facilitating conditions have a marginally significant impact on women's intention to use, while this effect is not significant for men. This suggests that the presence of necessary infrastructure and support is more important for women and could play a greater role in increasing their intention to use. Perceived benefits also significantly affect women's intention to use, while it has no impact on men, indicating the important influence of this variable on usage intention among women. Hedonic motivations do not significantly impact women's intention to use, which is a different result compared to men. Finally, effort expectancy significantly impacts women's intention to use, similar to men, showing that for both genders, ease of use and reducing the effort required to use electric vehicles play an important role in their intention to use them. Overall, the results show that some variables, such as performance expectancy and social influence, function similarly for both genders, while there are also gender differences in the importance of environmental concerns, facilitating conditions, and perceived benefits. This information can be useful for policymakers and urban planners in developing more effective strategies to promote the use of electric vehicles. These findings are presented in Table 6.

Table 6: Structural equation modeling (SEM) results (structural model) for women.

Hypothesis	Path	Coefficient	Standard Error	P-Value	Result
1	EA → UI	0.084	0.106	0.428	Not Supported
2	HM → UI	0.094	0.085	0.271	Not Supported
3	FC → UI	0.205	0.106	0.054	Supported
4	CE → UI	0.488	0.143	0.000	Supported
5	PE → PB	0.783	0.231	0.000	Supported
6	SI → PB	0.406	0.198	0.041	Supported
7	FM → UI	0.219	0.100	0.029	Supported

To examine the age-related heterogeneity in the adoption of shared electric vehicles, the participants were divided into two groups. The first group included young individuals aged 15 to 44 years. Middle-aged and older individuals were classified as those aged 45 years and above.

For the first group, consisting of young individuals (15-44 years), the results indicate that the impact of performance expectancy on perceived benefits is very strong and significant. This suggests that younger individuals place greater emphasis on the performance and efficiency of shared electric vehicles. Additionally, the impact of social influence on perceived benefits is also significant, highlighting the importance of social views and others' opinions in understanding the benefits of these vehicles for this group. Environmental concerns are also marginally significant for this group, indicating that environmental issues are of considerable importance to younger individuals. However, facilitating conditions are not significant for this group, suggesting that this variable does not hold the importance it should for younger individuals.

For the second group, consisting of middle-aged and older individuals (over 44 years), the results show notable differences. The impact of performance expectancy and social influence on perceived benefits is not significant in this group, indicating that older individuals do not pay as much attention to performance and social effects as younger individuals do. Environmental concerns and hedonic motivations are also not significant for this group, suggesting that these issues are of less importance to middle-aged and older individuals compared to younger people. However, facilitating conditions significantly impact usage intention, indicating that providing appropriate facilities and support can have a positive effect on the intention to use among older individuals. Overall, these results suggest that the factors influencing the adoption of shared electric vehicles vary between age groups. Younger individuals place more importance on performance, social influence, and environmental concerns, while older individuals focus more on facilitating conditions and efficiency. These differences can help policymakers and planners tailor their programs and strategies according to the needs and preferences of each age group. These findings are presented in Tables 7 and 8.

Table 7: Structural equation modeling (SEM) results (structural model) for young people.

Hypothesis	Path	Coefficient	Standard Error	P-Value	Result
1	EA → UI	0.154	0.082	0.062	Supported
2	HM → UI	0.230	0.086	0.008	Supported
3	FC → UI	0.081	0.081	0.316	Not Supported
4	EE → UI	0.418	0.111	0.000	Supported
5	PE → PB	0.750	0.210	0.000	Supported
6	SI → PB	0.524	0.205	0.091	Supported
7	PB → UI	0.127	0.075	0.091	Supported

Table 8: Structural equation modeling (SEM) results for middle-aged and elderly individuals.

Hypothesis	Path	Coefficient	Standard Error	P-Value	Result
1	EA → UI	0.06	0.098	0.526	Not Supported
2	HM → UI	0.023	0.082	0.779	Not Supported
3	FC → UI	0.225	0.102	0.028	Supported
4	EE → UI	0.205	0.079	0.01	Supported
5	PE → PB	3.21	4.93	0.515	Not Supported
6	SI → PB	4.54	5.18	0.38	Not Supported
7	PB → UI	0.205	0.079	0.01	Supported

6.3 Model Fit Evaluation

Several fit indices were used to evaluate the model fit in this study. These indices include the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), the normed chi-square (χ^2/df), and the Goodness of Fit Index (GFI).

The Chi-square test is one of the most commonly used tests in structural equation modeling. This test evaluates the difference between the observed covariance matrix and the covariance matrix predicted by the model [58]. A lower chi-square value indicates a better model fit. The value of $\rho \leq 0.05$ indicates a good fit of the model [59]. However, the Chi-square test is highly sensitive to sample size, meaning that in large samples, the chi-square value may become unfairly large, leading to the incorrect rejection of the model. Degrees of freedom refer to the number of independent observations used to estimate the model parameters. In structural equation modeling, degrees of freedom represent the difference between the number of observations (parameters in the covariance matrix) and the number of estimated parameters in the model. The normed chi-square (χ^2/df) is a metric used to assess the overall model fit. This ratio helps reduce the Chi-square's sensitivity to sample size [58]. A ratio value between 2 and 5 indicates a good model fit [58, 60]. This ratio shows how small the chi-square value is relative to the degrees of freedom, i.e., how well the model fits the data. The value of 2.47 calculated in this model indicates an appropriate model fit.

The Comparative Fit Index (CFI) is one of the important indices for evaluating the model, indicating how well the proposed model fits the observed data compared to the baseline model. A CFI value above 0.95 is generally considered a good fit. However, given the small sample size and the confirmation of other indices, the value of 0.913 obtained in this model is acceptable and indicates a relative fit of the model [61]. The Root Mean Square Error of Approximation (RMSEA) indicates the approximate error of the model in the population. An RMSEA value less than 0.05 is considered a very good fit, and a value between 0.05 and 0.08 is regarded as acceptable [44, 62]. The value of 0.07 obtained in this model indicates an acceptable fit.

Goodness of Fit Index (GFI) measures the relative amount of variance and covariance explained by the model. GFI values above 0.9 are generally acceptable and the value 0.911 calculated in this model suggests a good model fit [63].

7. Conclusions

These findings align with previous behavioral studies in transportation who demonstrated that user reactions to new or challenging conditions are crucial for designing effective mobility interventions. Likewise, understanding how potential users respond to shared electric vehicle programs provides valuable insights for policymakers and service providers [76]. This research confirms the significant impact of hedonic motivations on the adoption of shared electric vehicles, contributing to the extended Unified Theory of Acceptance and Use of Technology (UTAUT) [25]. It also examines the crucial role of perceived benefits in technology adoption [54, 64]. The results show that perceived benefits can mediate the effects of performance expectancy [54, 55]and social influence on the intention to use shared electric vehicles [65]. Performance expectancy positively influences perceived benefits, as users naturally expect more advantages when they believe a technology will perform well. Similarly, social influence positively affects perceived benefits, as others' opinions and behaviors shape users' perceptions [66]. For instance, if individuals observe friends and family benefiting from shared electric vehicles, they are likely to perceive these benefits more strongly themselves [67]. The variables "environmental awareness" and "hedonic motivations," which were added to the model, have been shown to significantly influence the intention to use shared electric vehicles [68, 69]. This research confirms that facilitating conditions play an essential role in enhancing the intention to adopt new technologies. It supports existing theories on technology adoption by highlighting the importance of providing adequate infrastructure and support [52, 53]. Additionally, the study demonstrates that perceived benefits positively and significantly affect the intention to use shared electric vehicles [70]. When users perceive substantial benefits, such as cost savings, time efficiency, and reduced traffic, they are more likely to adopt the technology [27, 54, 64, 71, 72]. Gender heterogeneity in the adoption of shared electric vehicles was also examined. The results of this examination showed that some variables, such as performance expectations and social impacts, affect both genders similarly, while there are also gender differences in the importance of environmental awareness, facilitating conditions, and perceived benefits. Age heterogeneity in the adoption of shared electric vehicles was also examined. The results showed that the factors influencing the adoption of shared electric vehicles differ between the two age groups. Younger individuals place more importance on performance, social impacts, and environmental concerns, while older individuals pay more attention to facilitating conditions and efficiency. These findings are consistent with broader behavioral transportation research who emphasized the crucial role of psychological factors in shaping drivers' behavior and decision-making processes in simulated environments. Likewise, this study confirms that behavioral and psychological dimensions play an essential role in shaping individuals' intention to adopt shared electric vehicles [77].

7. 1 Policy Implications

The results of this research can help urban policymakers and relevant officials to promote the use of shared electric vehicles in cities by emphasizing environmental benefits and creating suitable facilitative conditions [73]. Additionally, providing discounts and financial incentives can help increase the intention to use these vehicles [74, 75]. Companies offering shared electric vehicle services can increase the willingness to use these services by focusing on reducing the effort required and improving the user experience. Providing appropriate training and necessary support can help reduce users' concerns. This research shows that social impacts can play an important role in increasing the intention to use shared electric vehicles. Therefore, companies and organizations can increase the adoption of this technology by using advertising campaigns based on positive user experiences and supports from credible individuals. The results indicate that hedonic motivations play an important role in the intention to use shared electric vehicles. Therefore, companies can increase users' willingness to use these vehicles by offering attractive and enjoyable features in their vehicles, as well as providing a pleasant user experience. The results show that effort expectations significantly impact the intention to use shared electric vehicles. Therefore, the government should take measures to make the use of shared electric vehicles easier. This includes developing and improving mobile applications for reserving and using these vehicles, providing necessary training for new users, and facilitating the process of renting and returning vehicles. Additionally, in this research, environmental concerns were found to have a positive impact on the intention to use electric vehicles among men. Therefore, the government could implement educational programs and public awareness campaigns about the environmental benefits of using electric vehicles. These campaigns could include television and radio advertisements, social media, and educational programs in schools and universities. These suggestions and recommendations can help the government, by utilizing the results of this research, to develop more effective policies and programs to promote the use of shared electric vehicles in Tehran, thereby contributing to improved air quality and reduced traffic congestion.

7. 2 Limitations and future work:

This study has several limitations. First, data were collected using an online non-probability sampling method, which overrepresents younger and educated respondents. Second, the cross-sectional design cannot capture long-term behavioral changes. Third, the questionnaire included some items with low mean scores, suggesting possible wording issues or limited familiarity with SEVs. Finally, the study was conducted in a single developing city, and the findings may not be directly generalizable to other contexts. It is suggested that future studies should include expanding the data set and conducting more surveys to achieve greater accuracy in analyzing the impacts of various factors on the adoption and use of electric vehicles in different communities. This could be particularly useful in cities with varying environmental and social conditions. To improve the accuracy of the results and enhance the range of the data, it is suggested that future research use random sampling methods and conduct face-to-face interviews, aiming to collect a larger volume of data. Future studies should use probability-based methods and expand to multiple urban contexts. The importance of the perceived benefits variable in studies of shared electric vehicle adoption has been demonstrated, and this study confirmed it as well. However, this variable is often examined in separate components, such as safety, reduced economic costs, and decreased traffic congestion. A comprehensive examination of this variable under the broad category of perceived benefits can significantly aid in the adoption of shared electric vehicles. Additionally, investigating the factors influencing perceived benefits can contribute to a better understanding of users' perceived benefits.

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