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Travelers' Acceptance of Electric Carsharing Systems in Developing Countries: The Case of China

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Abstract: Emerging electric carsharing (EC) systems have demonstrated their advantages and attracted public attention. The number of EC systems is growing throughout the world, especially in metropolitan areas in developing countries. For successful implementation, developers need to understand the public acceptance of EC services. In this study, we sought to determine the factors that affect EC acceptance in the context of developing countries. The study involved 437 individuals, aged between 18 and 65 years, who were randomly sampled from an EC service area in China. The determinants of EC acceptance were investigated based on an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT) and tested by using Structural Equation Modeling. The results indicated that hedonic motivation (HM) has a powerful effect on behavioral intention (BI) to use the EC service in the future. Performance expectancy (PE), effort expectancy (EE), and familiarity with the carsharing concept (FM) also influenced EC's acceptance. However, the impact of social influence (SI) did not emerge from this study. The results also revealed that gender moderates the effects of EE and FM on BI. Age moderated the effect of FM on BI and unexpectedly moderated the impact of HM on BI. The present study confirmed the validity of the UTAUT research model in predicting the intention to use an EC system in developing countries. Implications and recommendations for government and EC developers are also discussed.

Keywords: electric carsharing (EC); UTAUT; public acceptance; developing countries; sustainable transportation

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1. Introduction

Nowadays, many metropolitan areas are implementing carsharing systems to manage urban mobility and traffic better. The number of countries that have implemented carsharing has increased, from 35 in 2014 (4.8 million members and 104,000 vehicles) to 46 in 2016 (15 million members and 157,000 vehicles) [1]. Carsharing is recognized as an alternative mode of transportation that would provide a solution to the rapid growth of car ownership and the negative consequences of urbanization such as traffic congestion, air pollution, and overloading of parking lots [2–5]. Recently, more and more countries have considered using electric carsharing (EC) systems to achieve sustainable urban mobility. Similar to traditional carsharing services, EC systems allow people to rent a shared vehicle for a short period, usually by the hour. EC provides one-way (enables users to pick up and drop off the shared vehicle at different stations) and free-floating (allows users to pick up and leave the sharing vehicle anytime and anywhere within a predefined service area) services, but using a fleet of electric vehicles instead of fuel vehicles. EC systems have been operating in both the developed and developing countries, such as Japan, the Netherlands, Spain, the USA, Korea, and China [6]. However, the use of EC services was limited for some time due to several technology-related reasons, such as the poor reliability of vehicles (e.g., the short lifetime of the battery) and a lack of charging points [7]. These disadvantages have led to a decrease in people's acceptance of the EC service. Given that users' acceptance is a fundamental factor in the development and success of a service, it is essential to understand the factors that determine the public acceptance of EC systems.

In previous studies, carsharing preference is predicted based on the factors of carsharing attributes (e.g., price, type of vehicle, access distance, or availability of the vehicle) and users' socio-demographic characteristics [8–11]. Research has shown that price, parking convenience, and car type were the significant factors influencing individuals' preferences [5,9,12]. Previous research has also found that young people, men, well-educated, and moderate-income people were more interested in the carsharing system [13–15]. Another study has found the same indicators for the services in China [16]. Furthermore, people's awareness of environmental issues has also been identified as one of the main factors that affect willingness to join carsharing services [17,18].

Although electric vehicles do not have the problems of CO_2 emissions and fossil fuel dependence involved in gas cars, they reduced the attractiveness of carsharing services for potential users [19]. This situation has led developers to ask the question of "can we to change people's attitude toward the EC service?" As stated by Fleury et al. [20], to change people's attitudes and perceptions about carsharing service, we need to identify the essential determinants that constitute their intention. Some studies have considered respondents' attitudes and perceptions to classify potential user segments. Efthymiou et al. [21] conducted a study in Greece and suggested that taxi clients, public transportation users, and those who care about environmental issues were the most likely to join a carsharing service. The satisfaction of respondents with their current mode of travel has also been considered to model the propensity to join a carsharing scheme. Efthymiou and Antoniou [22] found an increase in the likelihood to use carsharing for people who are less satisfied with their mobility patterns. Paundra et al. [23] have conducted a study in the Netherlands to examine the moderating effect of psychological ownership factors on the relationship between respondents' acceptance and necessary car attributes (e.g., price, parking convenience, or car type) [23]. They found that not only do the car attributes impact preferences for carsharing services, but also the psychological ownership of potential customers plays an essential role in increasing the preference for a shared car. More recently, Fleury et al. [20] considered the use of psychological factors to describe the determinants of users' behavioral intention towards a corporate carsharing service in France. They found that people's intention to use a carsharing service depends on their perception of the services—factors such as perceived usefulness, perceived ease of use, and perceived environmental friendliness. Overall, the literature indicates that a small number of studies on carsharing acceptance examined psychological factors. Furthermore, most of these studies are from developed countries, where motorization is complete.

Even though there is an increase in attention to emerging transportation modes, there are fewer EC studies from developing countries. Most of the carsharing research from developing countries has focused on market growth and operational aspects rather than the behavioral aspect [24–28]. Similar to other modes of transportation, acceptance of EC is also likely to vary according to cultural factors in different regions of the world. For example, compared to other countries, EC use might be less attractive in China due to a cultural preference toward car ownership among Chinese people. Therefore, it is essential to conduct EC acceptance studies in countries with a different cultural profile. To our knowledge, no study has attempted to use psychological factors to explore individuals' acceptance of an EC system in developing countries. The present study thus attempts to fill this knowledge gap by investigating EC acceptance in China, where increasing EC use might be an efficient tool to mitigate the increase in car ownership and associated environmental issues.

Dalian, China was selected as the case city in which to conduct this study. Dalian is the second-largest city in Liaoning province in Northeast China. As of 2016, Dalian had a total administrative area of 12,573 km^2 and a population of 5.9 million people. The Dalian urban density is 1550 per km^2. At the same time, the city's GDP registered a 6.5% increase, reaching 652.7 billion RMB [29]. Dalian has a comprehensive public transport system. There are hundreds of bus lines, three trolleybus lines, and four subway lines in the city. The total number of passengers of the public transportation systems reached 962 million in 2016. There are not many bicycles in Dalian because of the steep terrain. Selling and using motorcycles in the city is also prohibited. However, the number of private cars on Dalian streets has increased rapidly in recent years. There were 1.2 million cars on the city's roads in 2016, causing an increase in traffic congestion. In July 2017, the first EC system launched in Dalian City, namely "Qingke Chuxing" (https://www.reachstar.cn). In the first stage, the system operated a fleet of 100 electric vehicles and had four smart charging spots distributed across Gaoxin district (see Figure 1). The EC company also has a plan to increase the vehicle fleet to 300, which can provide travel services for about 8000 people per day. The EC system was expected to help reduce the negative consequence of private cars (e.g., traffic congestion and air pollution) in the area. Since Dalian has a high motorization rate and high urban density, it can be considered as a potential market for the EC system. However, it is still too early to confirm the benefits an EC system will bring to the ara. As discussed above, there is a need to investigate the factors affecting travelers' acceptance of EC, as well as formulate reasonable policies for successful EC implementation in the future.

Thus, the first aim of this study is to identify the most significant factors that determine users' intention to use the EC system by employing the unified theory of acceptance and use of technology (UTAUT) model [30]. The second aim is to compare the effect of these factors among multiple groups, such as age and gender. The third aim is to provide policies for future adoption of EC systems in the context of developing countries.

The following section provides a brief introduction to acceptance model concepts, which is a basis for exploring the determinants of users' intention to use the EC service in this study. Data and methods are discussed in Section 3. Section 4 presents the results. The paper then closes with a brief discussion in Section 5 and the conclusions in Section 6.

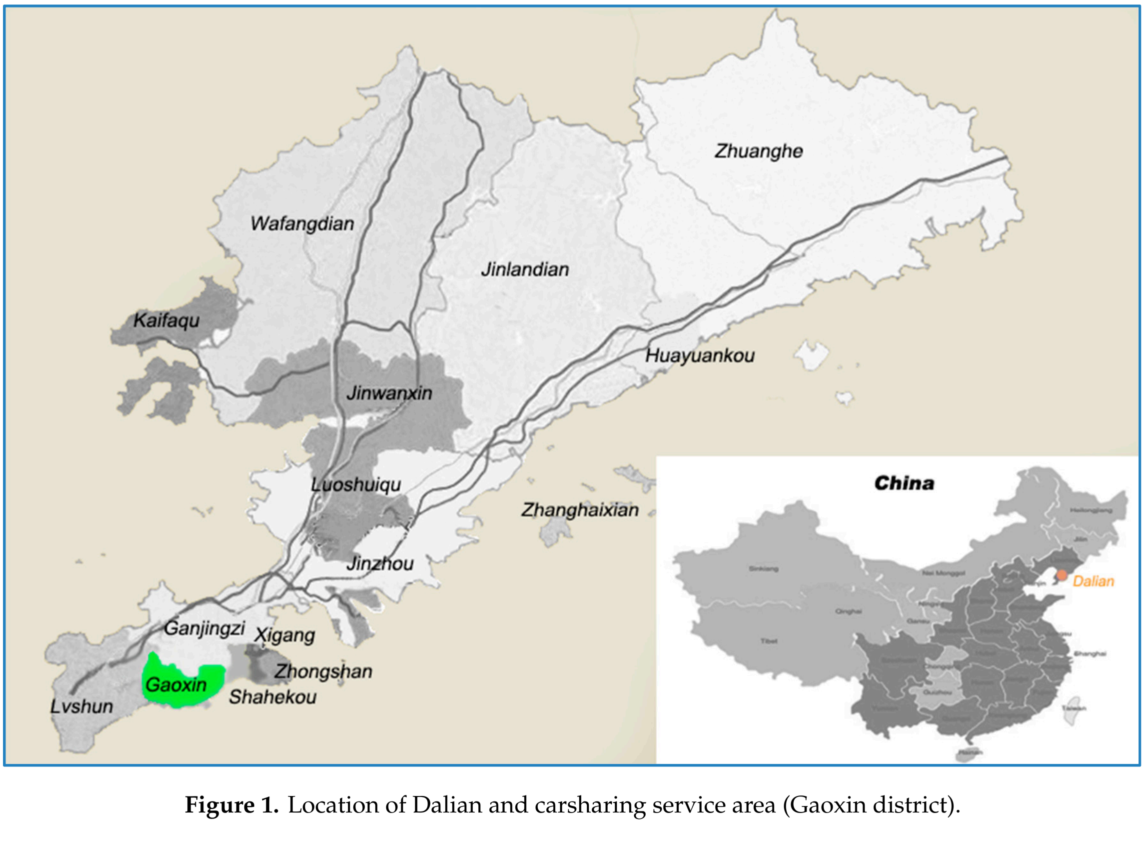

Figure 1. Location of Dalian and carsharing service area (Gaoxin district).

2. Theoretical Background and Research Hypotheses

2.1. Acceptability and UTAUT Model

Human behavioral scientists have developed several theoretical methods to explore individuals' adoption of technology and its determining factors. The dominant models have been widely used in the past decades, such as the theory of reasoned action (TRA) [31], the technology acceptance model (TAM) [32], the theory of planned behavior (TPB) [33], and the unified theory of acceptance and use of technology (UTAUT) [30]. These models posit that the actual use can be predicted by the structure of intention to use.

The theory of reasoned action posits the influence of beliefs and perceived subjective norms on behavior [31]. The TAM and TPB models were built on the TRA model to examine the factors affecting individuals' acceptance and human behavior, respectively. TAM represents the relationships between perceived usefulness, perceived ease of use, and intention to use new technology [32]. The TPB model explains how the attitude toward the behavior, subjective norm, perceived behavior control, and behavioral intention are related to actual behavior [33]. In order to fully explain the acceptance, Venkatesh et al. [30] proposed the UTAUT model as an extension of TAM to explain users' intention to use an information system (IS) and their actual behavior. The model has suggested four determinants of behavioral intention (BI) and usage behavior, including performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating condition (FC). The UTAUT posits that PE, EE, and SI predict BI, which, in turn, together with FC determines actual usage behavior (see Figure 2) [30]. Since its introduction, UTAUT was widely applied to many fields of research, such as studies on e-commerce [34,35] and the medical field [36–39].

The UTAUT model has also been adopted in the field of transportation research. For instance, Rahman et al. [40] used UTAUT to examine drivers' acceptance of navigation technology, namely the advanced driver assistance system (ADAS). They found that performance expectancy, effort expectancy, and social influence together predicted the intention to use ADAS with high accuracy. In the study of Wolf and Seebauer [41], the UTAUT model was adopted to classify the early Austrian adopters and their reasons for using electric bicycles. They have enriched the UTAUT model with additional factors taken from research on travel mode choices such as personal norms, trip distance, or attitude toward physical activity. Madigan et al. [42] extended the UTAUT to predict behavioral intentions in the context of autonomous vehicles. The study examined the impact of facilitating conditions on behavioral intentions and have also accounted for the impact of hedonic motivation, which is discussed in the study of Venkatesh et al. [43]. Their study indicated that performance expectancy, social influence, facilitating conditions, and hedonic motivation together successfully predicted the behavioral intention to adopt ARTS (automated road transport system) vehicles in Trikala, Greece. However, they failed to find a significant impact of moderating factors of the UTAUT model, including age, gender, and experience, which was proposed in the study of Venkatesh et al. [30].

Regarding the context of carsharing services, Fleury et al. [20] have investigated UTAUT by using structural equation modeling. They examined the impact of PE, EE, FC, and perceived environmental friendliness on behavioral intentions toward a corporate carsharing service. Their model has shown that effort expectancy was an essential factor in predicting behavioral intentions towards carsharing in a company. Furthermore, the facilitating condition and perceived environmental friendliness also had an impact on behavioral intention through effort expectancy and performance expectancy, respectively. In line with the studies of Madigan et al. [42,44], the moderating effects of age, gender, and experience also did not emerge from their study.

Generally, the above research findings on the UTAUT model suggested that it can be applied to public acceptance of new technology transport modes such as electric vehicles, autonomous vehicles, or even EC systems. Therefore, it is feasible to apply the UTAUT model to investigate the factors affecting individuals' acceptance of EC systems.

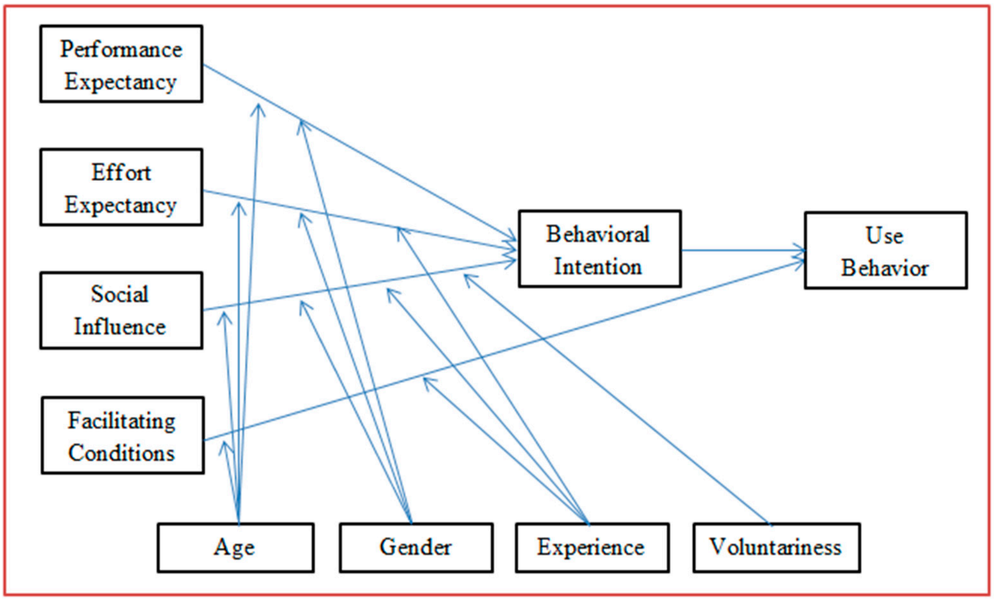

Figure 2. The original UTAUT model [30].

2.2. Research Model and Hypotheses

The current study attempted to predict the behavioral intention towards an EC system. We extend the UTAUT structure by investigating the additional impact of hedonic motivation and familiarity with the carsharing concept on behavioral intention. We also examined the effect of moderating factors, age, and gender, as was discussed in the study of Venkatesh et al. [30]. Since EC is relatively new to the study area, users' experience is still limited. Furthermore, not every traveler may consider its adoption. Hence two UTAUT moderators, voluntariness and experience, are not considered in this study. This study is also distinguished from previous studies on the carsharing system in its focus on the public acceptance of EC services in the context of a developing country (China).

Furthermore, although previous studies have modified the original UTAUT model by involving the influence of facilitating condition on behavioral intention rather than on use, few studies showed a strong relationship between the two dimensions. The relationship was first supported by the study of Venkatesh et al. [43] in the context of mobile internet technology. In the transportation arena, Madigan [42] found little effect of facilitating condition on users' intention to use autonomous vehicles. However, in the context of a corporate carsharing system, Fleury et al. [20] found that facilitating condition only partially mediated the effect of effort expectancy on behavioral intention. Therefore, similar to previous studies [44–46], we decided not to examine the effect of facilitating condition on behavioral intention to use EC. The proposed research model is given in Figure 3.

2.2.1. Performance Expectancy of EC

Venkatesh et al. [30] defined performance expectancy as the degree to which an individual believes that using new technology can improve his/her job performance. This construct has been shown to have a strong effect on technology acceptance [30,42,47]. In the context of carsharing systems, performance expectancy refers to the match between system features and travelers' expectations, implying that the user realizes benefits from sharing vehicles. Previous studies on users' preference for a carsharing system have shown that a carsharing system could help travelers with travel planning, save them time, and meet their automobile needs, which, in turn, could enhance their job performance [5,8]. Furthermore, a shift from conventional cars to EC is associated with many other benefits, such as reduced energy use, air pollution, and traffic congestion [3,4,48]. Fleury et al. [20] concluded that performance expectancy is a critical factor for predicting users' intention to adopt a corporate carsharing system. This relationship has also been confirmed by studies on user acceptance of autonomous vehicles [42,45,49] and electric vehicles [41,50]. Therefore, we hypothesize:

Hypothesis 1 (H1). *The performance expectancy positively influences the behavioral intention to use EC.*

2.2.2. Effort Expectancy of EC

Effort expectancy, also called perceived ease of use in TAM, refers to the perception that using a system is free from effort [47]. Using EC is associated with the use of related mobile phone technologies (e.g., e-reservation, e-payment) and new technology in an electric vehicle. Since the EC is easy to use and easy to interact with, individuals' intention to use will be increased. The relevance of effort expectancy was confirmed for both new technology adoption [38,46–48] and mobility behavior [45,49,51,52]. Furthermore, previous studies on carsharing have proven that effort expectancy is one of the core determinants of users' intention to use the system [20]. Thus, we hypothesize:

Hypothesis 2 (H2). *Effort expectancy has a positive effect on behavioral intention to use EC.*

2.2.3. Social Influence on EC

Social influence is defined as the extent to which an individual perceives that it is important for others to believe that s/he should use new technology [30]. Although social influence is a key determinant of behavioral intention, previous empirical studies have shown an inconsistent interaction between the two constructs. Many researchers have proven that social influence has a significant effect on the intention to use new technology [37,42,43,53], but some others found that the relationship is insignificant [20,46,54]. Venkatesh et al. [30] also suggested that social influence only works for some people, such as older workers and women. However, in the context of transportation, many previous studies have shown the significant role of social influence in predicting individuals' acceptance of transportation-related alternatives, such as travel mode use [42,55,56], or road pricing strategies [57]. In the context of an EC system, individual behavior is influenced by the way colleagues, friends, or family members value the use of the service. Furthermore, Algesheimer et al. [58] mentioned that the interaction between carsharing users and others is essential for engagement and recommendations. Therefore, we hypothesize:

Hypothesis 3 (H3). *Social influence has a positive effect on behavioral intention to use EC.*

2.2.4. Familiarity with the Carsharing Concept

Gefen [59] stated that "familiarity deals with an understanding of the current actions of other people or objects." People's familiarity with a specific system is formed by previous interactions, experiences, or learning of knowledge related to the use of the system. Previous studies on consumers' acceptance of e-commerce have shown the strong influence of people's familiarity on their intention to purchase [59,60]. In the case of using carsharing services, familiarity is characterized by several attributes, such as people's knowledge learned from social media systems (e.g., carsharing is an innovative transport mode), experience of related technologies (e.g., mobile banking, electric vehicle), and other similar concepts (e.g., bike-sharing, conventional carsharing, pool-sharing). The familiarity would reduce complexity through an understanding of how to use the system. A previous good experience with a carsharing system and its services (e.g., access distance, ease of use, vehicle availability) should cause an individual to develop concrete and favorable ideas of what to expect in the future. Previous studies on travelers' preferences for carsharing systems have found that the increase in people's knowledge about carsharing is consistent with an increase in their likelihood to join the services [22,24]. Thus, in this study, we expect that an individual who is familiar with the carsharing concept would have a positive intention to use electric carsharing in the future. Therefore, we hypothesize:

Hypothesis 4 (H4). *Familiarity with the carsharing system has a positive effect on behavioral intention to use EC.*

2.2.5. Hedonic Motivation toward EC

Hedonic motivation is also conceptualized as perceived enjoyment. It is the fun or enjoyment derived from using a technology [43]. The relationship between hedonic motivation and behavioral intention has been shown in many previous studies on technology acceptance [42,61–63]. In this study, the hedonic motivation refers to the extent to which the activity of using the EC or its innovation concept is perceived to be enjoyable. Madigan et al. [42] confirmed that the fun and entertainment that people get from using a specific transport mode leads to increased intention to use. Moreover, a previous study on carsharing has also suggested that fun can be derived from the distinct design of sharing vehicles such as the visible label and small size of the cars [15]. Thus, we expect that individuals with a positive hedonic motivation (or perceived enjoyment) toward EC are also likely to have a more positive intention to use the system, especially since EC is a relatively new transport mode. We hypothesize:

Hypothesis 5 (H5). *Hedonic motivation has a positive effect on the behavioral intention to use EC.*

2.2.6. Moderating Effect of Age and Gender

As discussed above, in this study, we examine the effect of the two UTAUT moderators, gender, and age [30]. The literature has provided evidence that people in different age groups or of different genders would have different behavior regarding new technology adoption [30,43,64].

First, regarding age groups, previous studies have underlined the importance of the users' age in determining their behavior. For example, studies on the acceptance of electric vehicles have shown a positive association between older consumers and the intention to use e-bikes [41,56]. In relevant UTAUT research, the moderating effects of age on the relationships among constructs were confirmed in different contexts, such as information technology (IT) [54,64,65] and e-commerce [66,67]. Overall, these studies have shown inconsistent results regarding the age moderator in the UTAUT model. For instance, in the field of IT, the effect of effort expectancy on behavioral intention is stronger for older users [64], while it was not different among the age groups in another context such as mobile technology adoption [68]. Although no UTAUT research has demonstrated the moderating effect of age groups on behavioral intention to use carsharing systems, several stated preference studies have shown that younger people are more likely to engage with carsharing services [8,21,69]. A high ability to use new technology (e.g., smartphone applications and electric vehicles) might explain the stronger intention to use carsharing among young people. This leads younger individuals to gain more significant experience with carsharing. The effects of performance expectancy and familiarity thus are expected to be stronger in younger people than in older people. On the other hand, older individuals with a lack of experience would worry more about ease of use in comparison to other transport modes (e.g., buses, taxis, conventional cars). Older individuals are also expected to be more strongly affected by social influence, as the needs for affiliation increase with age [70]. Furthermore, research in psychology has found that the effect of hedonic motivation on behavioral intention is stronger for younger individuals than for older ones [71,72]. This relationship is also supported by Venkatesh et al. [43]. Therefore, we hypothesize:

Hypothesis 6a (H6a). *The effect of performance expectancy on behavioral intention to use EC is stronger for younger individuals.*

Hypothesis 6b (H6b). *The effect of effort expectancy on behavioral intention to use EC is stronger for older individuals.*

Hypothesis 6c (H6c). *The effect of social influence on behavioral intention to use EC is stronger for older individuals.*

Hypothesis 6d (H6d). *The effect of familiarity with carsharing on behavioral intention to use EC is stronger for younger individuals.*

Hypothesis 6e (H6e). *The effect of hedonic motivation on behavioral intention to use EC is stronger for younger individuals.*

Second, regarding gender, behavioral differences between males and females have been found by previous studies on economics and psychology in several dimensions, such as social preferences [73], customer loyalty [74], and technology acceptance [75]. In terms of carsharing, gender differences have also been shown in previous empirical studies [14,15], in which males were found to be more interested in carsharing services than females. However, these studies did not reveal what is responsible for this gap between males and females in carsharing adoption. Recently, Kawgan-kagan et al. [76] found that females use carsharing less than males because of gender roles (e.g., childcare, household duties, and shopping trips). Thus, we expect that the relationship between the intention to use EC and its determinants will be moderated by gender. Since females tend to be more sensitive to others' opinions [64], social influence is expected to be more salient when forming an intention to use EC. The effect of performance expectancy on behavioral intention to use EC is expected to be stronger for men because of gender roles. For example, women with children are less interested in carsharing services in comparison with men [76]. Research on gender differences also suggests that men tend to be more familiar with new technology than women [77]. Therefore, the effects of familiarity and hedonic motivation on behavioral intention are expected to be stronger for men, while effort expectancy is expected to be more salient for women. The moderating effect of gender in the UTAUT model was confirmed by previous studies in several contexts, such as information technology [30,43,64], educational technology [65], and mobile banking [66]. Therefore, we hypothesize:

Hypothesis 7a (H7a). *The effect of performance expectancy on behavioral intention to use EC is stronger for men.*

Hypothesis 7b (H7b). *The effect of effort expectancy on behavioral intention to use EC is stronger for women.*

Hypothesis 7c (H7c). *The effect of social influence on behavioral intention to use EC is stronger for women.*

Hypothesis 7d (H7d). *The effect of familiarity with carsharing on behavioral intention to use EC is stronger for men.*

Hypothesis 7e (H7e). *The effect of hedonic motivation on behavioral intention to use EC is stronger for men.*

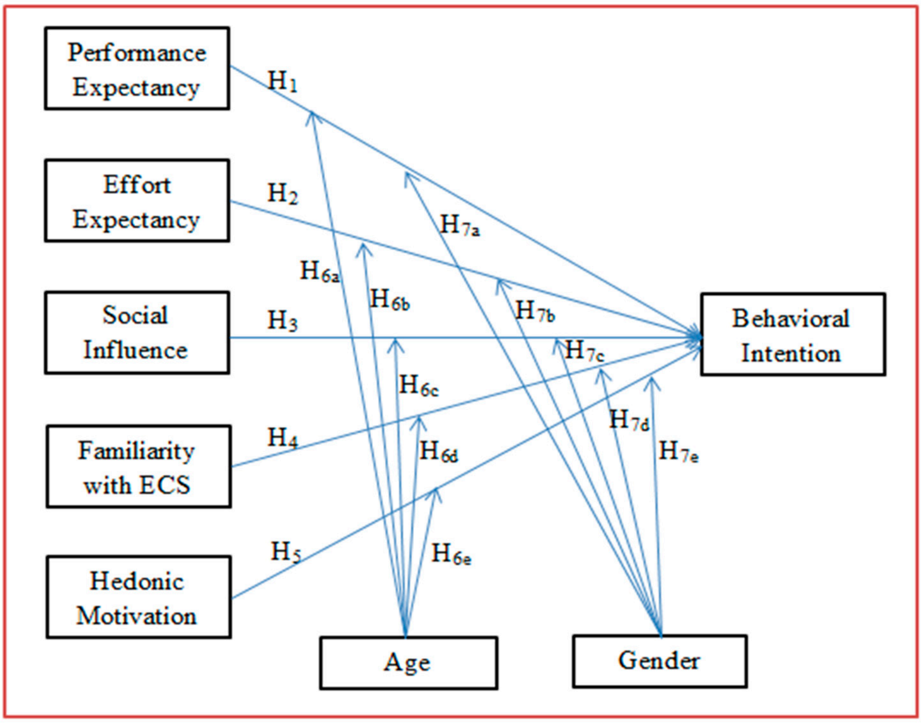

Figure 3. Research-modified UTAUT model.

3. Methods

3.1. Survey Design and Measurements

The survey was designed to capture information about the constructs in the proposed model. We divided the questionnaire into two parts. The first part requests respondents' demographics and trip preferences, such as current mode choice, car ownership, and carsharing experience. The second part contains a number of items that are used to measure the proposed UTAUT dimensions. The items of performance expectancy, effort expectancy, social influence, and behavioral intention were adopted from Fleury et al. [20], Venkatesh et al. [30], and Madigan et al. [42]. The items of hedonic motivation were taken from Venkatesh et al. [39] and Madigan et al. [42]. The items of familiarity with the carsharing concept were modified based on the studies of Gefen [59] and Kim et al. [60]. The questionnaire was translated into Chinese by the authors and independently checked by a bilingual colleague who works at the School of Foreign Languages, Dalian University of Technology to ensure that the meanings have been correctly translated. A pilot survey with 20 respondents was carried out with a questionnaire of 26 items to ensure the validity of all the scale items. Based on the results of the pilot study and a further literature review, the questionnaire was reduced to 21 items (see Table 1), with all items measured using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree."

3.2. Participants

The study was conducted in Dalian, a financial center and motorized city in the northeast of China. The random sampling strategy was used in this study. The EC was described to participants as a new transport mode. In order to increase content validity, participants should have some knowledge of the carsharing concept before answering the questionnaire. Therefore, a one-page brochure was included in the questionnaire, which clearly describes the concept of the EC system to the participants.

Two data samples were collected. The first sample was collected from 15 to 31 December 2018; the second was collected from 4 April to 7 May 2019. The questionnaires were distributed using an online form (https://www.wjx.cn). Each questionnaire took the respondent between 7 and 15 min to finish. After eliminating incomplete and invalid responses (e.g., respondents who took less than seven minutes to complete the questionnaire were removed from the sample), we obtained a sample of 437 participants (200 respondents from sample 1, and 237 respondents from sample 2). The Kolmogorov-Smirnow (K-S) test [78] was adopted to test the difference between the two sample distributions. As can be found from Table 2, except for a few items, the distribution of the two samples was similar ($p > 0.05$), indicating that the response bias in the research data could be excluded. The total sample was 44.9% male and 55.1% female. The sample's age distribution is quite young; participants whose age ranged from 18 to 35 years accounted for 80.1%. The majority of the respondents had a valid driver's license (78%), and 80.8% of respondents were college graduates or higher. Although the EC service had been introduced about one year before the time of this study, only 73 respondents (16.7%) were users of the service. The descriptive statistics of the sample are detailed in Table 3.

Table 1. The items of modified UTAUT constructs.

Constructs	Items	Description	Source
Performance Expectancy (PE)	PE1	I would find the EC service useful for my travel.	[20,30]
	PE2	I think using a shared electric vehicle in my day-to-day commuting would be better and more convenient than my existing form of travel.	
	PE3	I think using EC will enhance my productivity in my job.	
	PE4	I think using EC will help me save travel time.	
Effort Expectancy (EE)	EE1	I would find EC easy to use.	[20,30]
	EE2	It would not take me long to learn how to use an electric sharing vehicle.	
	EE3	My interaction with EC would be clear and understandable.	
	EE4	It would be easy for me to become skillful at using the EC system.	
Social Influence (SI)	SI1	People who influence my behavior think that I should use EC for my daily travel.	[20,30]
	SI2	I think I am more likely to use the EC system if my friends and my family use it.	
	SI3	I use EC because of my colleagues who use the system.	
Hedonic Motivation (HM)	HM1	I think using EC is fun.	[43]
	HM2	I think using EC is entertaining.	
	HM3	I think using EC is enjoyable.	
Familiarity with Carsharing (FM)	FM1	I am familiar with carsharing services from reading the newspaper/social media.	[60,61]
	FM2	I am familiar with searching for carsharing on a smartphone application.	
	FM3	I am familiar with the process of reservation and payment for the carsharing system.	
	FM4	I am familiar with driving an electric sharing vehicle.	
Behavioral Intention (BI)	BI1	I intend to use the EC system in the next six months for some of my daily travel.	[20,30]
	BI2	I predict I will use the EC in the next six months.	
	BI3	As soon as I am able, I will use the EC service.	
	BI4	I plan to use the EC service each time I need it for business travel.	

Table 2. Sample distribution and Kolmogorov-Smirnov test.

Items	Total (n = 437)		Sample 1 (n = 200)		Sample 2 (n = 237)		Kolmogorov-Smirnov Test	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Z**	**p**
PE1	3.90	0.873	4.00	0.811	3.83	0.916	0.811	0.526
PE2	3.41	1.022	3.59	0.947	3.26	1.06	1.504	0.022
PE3	3.39	0.946	3.55	0.873	3.27	0.988	1.317	0.062
PE4	3.53	0.922	3.66	0.860	3.43	0.961	1.226	0.099
EE1	3.51	0.913	3.56	0.895	3.46	0.927	0.73	0.661
EE2	3.80	0.828	3.81	0.843	3.80	0.817	0.276	1.000
EE3	3.82	0.824	3.86	0.817	3.79	0.831	0.473	0.979
EE4	3.80	0.836	3.85	0.839	3.77	0.834	0.385	0.998
SI1	3.58	0.904	3.71	0.836	3.46	0.945	1.001	0.269
SI2	3.81	0.828	3.95	0.752	3.70	0.874	1.312	0.064
SI3	3.74	0.860	3.88	0.795	3.62	0.896	1.171	0.129
HM1	3.54	0.855	3.63	0.894	3.46	0.815	1.635	0.010
HM2	3.48	0.800	3.57	0.812	3.41	0.785	1.345	0.054
HM3	3.48	0.791	3.61	0.762	3.37	0.800	1.625	0.010
FM1	3.34	1.007	3.34	1.014	3.34	1.003	0.073	1.000
FM2	3.45	0.998	3.44	1.005	3.46	0.993	0.065	1.000
FM3	3.43	0.990	3.41	0.998	3.45	0.984	0.209	1.000
FM4	3.34	0.991	3.32	0.995	3.36	0.988	0.191	1.000
BI1	3.11	1.089	3.24	1.057	2.99	1.105	1.477	0.026
BI2	3.06	1.114	3.20	1.101	2.95	1.115	1.200	0.112
BI3	3.30	1.040	3.52	0.951	3.11	1.077	2.221	0.000
BI4	3.14	1.059	3.31	1.029	2.99	1.064	1.501	0.022

Note: SD = standard deviation; Z = Kolmogorov-Smirnov Z values; p = probability value.

3.3. Analysis Procedure

As discussed above, the present study examines the determinants of behavioral intention to use an EC system. The relationship between psychological factors (latent variables) of the research model has been hypothesized in Section 2.2. Structural equation modeling (SEM) is the most common analysis technique to test the hypotheses about causal relationships between latent variables. In general, SEM investigates the relationships between latent factors, which are measured by several consistent items. The advantages and limitations of SEM are discussed in detail in the literature [79]. As a prerequisite to SEM, the assignment of items to factors (measurement model) and the discriminant validity of all latent factors are tested with confirmatory factor analysis (CFA) [80]. Therefore, the proposed research model was tested using a two-step approach [81]. This is consistent with previous UTAUT research [20,54,65]. In the first step, CFA is conducted to assess the reliability and validity of the constructs. In the second step, SEM is employed to test the hypothesized relationships among the constructs of the research model. The R program and lavaan package [82] were used as the data analysis tool. Since all items in the data are nearly normally distributed based on the Skewness and Kurtosis indexes (Appendix A), the maximum likelihood is adopted as an appropriate method to estimate the CFA and SEM used in this study [80].

A multigroup comparison (e.g., younger vs. older; males vs. females) is employed [41,83,84] to test whether age and gender moderate the impact of various predictors on the intention to use EC. The two age groups were split based on the demographics of potential carsharing customers, as suggested in the previous study [85]. The first group (the younger group) included respondents aged between 18 and 25 (n = 146) and the second group (the older group) included respondents over 26 (n = 291). The measurement invariance test was first used to ensure the validity of the multigroup comparison. An insignificant chi-square result indicates invariance between groups of the measurement model. As the next step, to investigate which effects in the model are moderated by age and gender, single paths were constrained one at a time to be equal in both (age and gender) groups. A significant difference between unconstrained and constrained models would indicate a moderating role of moderator variables on a specific path [83].

Table 3. Social demographic characteristics.

Demographic	Category	Frequency	Percent (%)	Cumulative Percent (%)
Gender	Male	196	44.90	44.90
	Female	241	55.10	100
Age	18–25	146	33.40	33.40
	26–35	204	46.70	80.10
	36–45	68	15.60	95.70
	46–55	14	3.20	98.90
	>55	5	1.10	100
Education	High school	32	7.30	7.30
	Vocational school	20	4.60	11.90
	Bachelor's	209	47.80	59.70
	Graduate	176	40.30	100
Family status	Single	137	31.40	31.40
	Married with children	159	36.40	67.60
	Married without children	43	9.80	77.60
	Living with parents	88	20.10	97.70
	Other	10	2.300	100
Income	≤5000 RMB	244	55.80	55.80
	5001–10,000 RMB	99	22.70	78.50
	10,001–15,000 RMB	42	9.60	88.10
	15,001–20,000 RMB	21	4.80	92.90
	>20,000 RMB	31	7.10	100
Car ownership	None	109	24.90	24.90
	1 Car	228	52.20	77.10
	≥2 Cars	100	22.90	100

Note: 1 RMB = 0.415 USD (March 2019).

4. Results

4.1. Measurement Model

The properties of the measurement model were evaluated by testing the reliability, convergent validity, and discriminant validity. The value of composite reliability (CR) for all constructs (see Table 4) was higher than 0.6, thereby confirming the reliability of the model [86]. Table 4 shows that the factor loadings of all items except EE1 and BI4 were higher than 0.5 (EE1 and BI4 were removed from the constructs because their loadings lower than 0.5), and the values of average variance extracted (AVE) were also higher than 0.5, confirming the convergent validity of the model [87]. In Table 5, the square root of AVE for each construct (diagonal values) were higher than interconstruct correlations (off-diagonal values), indicating discriminant validity for the model [88].

Several goodness-of-fit indices are used to evaluate the model fit of the CFA. An insignificant result of the chi-square test ($p > 0.05$) indicates a good fit of the model [89,90]. However, the chi-square statistic is too sensitive to sample size, which means that this test nearly rejects the model when large samples are used (e.g., a sample size of 400 or more) [91]. An alternative approach is used to minimize the impact of sample size, namely normed chi-square (χ^2/df) [92]. A normed chi-square value between 2 and 5 is considered an acceptable fit [92,93]. Other indices can also be used, such as the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The values of 0.95 or higher for CFI and TLI [94], and lower than 0.06 and 0.08 for RMSEA and SRMR, respectively, indicate a good fit of the model [80,94]. All fit indices of the measurement model in Table 4 (χ^2 = 357.868, df = 153, $p < 0.001$; χ^2/df = 2.33; CFI = 0.969; TLI = 0.961; RMSEA = 0.055; SRMR = 0.055), except the chi-square statistic ($p < 0.001$) satisfied the recommended thresholds, thereby indicating that the model fits the data.

Table 4. Validity and reliability of the measurement model.

Constructs	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
Performance Expectancy (PE)	PE1 PE2 PE3 PE4	0.731 0.774 0.885 0.864	0.889	0.887	0.667
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	dropped 0.752 0.899 0.895	0.883	0.886	0.725
Social Influence (SI)	SI1 SI2 SI3	0.780 0.859 0.883	0.876	0.877	0.704
Hedonic Motivation (HM)	HM1 HM2 HM3	0.765 0.888 0.905	0.887	0.887	0.724
Familiarity with carsharing concept (FM)	FM1 FM2 FM3 FM4	0.780 0.918 0.886 0.783	0.904	0.907	0.712
Behavioral Intention (BI)	BI1 BI2 BI3 BI4	0.930 0.933 0.649 dropped	0.867	0.887	0.730

Note: Model measurement fits: $\chi^2 = 357.868$, df = 153, $p < 0.001$; χ^2/df = 2.33; CFI = 0.969; TLI = 0.961; RMSEA = 0.055; SRMR = 0.055, CR = composite reliability, AVE = average variance extracted.

Table 5. Correlations and the square root of AVEs (diagonal) of constructs.

	PE	EE	SI	HM	FM	BI
PE	0.817					
EE	0.525 **	0.851				
SI	0.649 **	0.639 **	0.839			
HM	0.757 **	0.624 **	0.677 **	0.850		
FM	0.196 **	0.221 *	0.210 *	0.321 **	0.844	
BI	0.561 **	0.535 **	0.512 **	0.628 **	0.285 **	0.854

Note: * Significant at the 0.05 level (two-tailed); ** Significant at the 0.01 level (two-tailed).

4.2. Structural Model

Table 6 represents the results of the path analyses with standardized coefficients. Similar to CFA, the structural equation modeling (SEM) result indicates that the model fits the data (χ^2 = 357.686, df = 153, $p < 0.001$; χ^2/df = 2.33; CFI = 0.969; TLI = 0.961; RMSEA = 0.055; SRMR = 0.055). Performance expectancy (PE) positively affected the behavioral intention (BI) to use EC ($\beta = 0.174$, $p < 0.05$), confirming H1. The effect of effort expectancy (EE) on BI was also significantly positive ($\beta = 0.204$, $p < 0.01$), providing support for H2. Meanwhile, social influence (SI) did not show any influence on BI ($\beta = 0.036$, $p > 0.05$), so H3 is not confirmed. These results were partially consistent with the original UTAUT model [30]. The two new constructs in the proposed model, hedonic motivation (HM) and familiarity with the carsharing concept (FM), have a positive impact on BI, providing empirical support for H4 ($\beta = 0.313$, $p < 0.01$) and H5 ($\beta = 0.097$, $p < 0.05$), respectively. Altogether, our research model explained 45% of the variance in behavioral intention.

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

Hypotheses	Path	Coeff.	SE	*p*-Value	Results
H1	PE → BI	0.174	0.124	0.018	Supported
H2	EE → BI	0.204	0.098	0.001	Supported
H3	SI → BI	0.036	0.098	0.601	Not supported
H4	HM → BI	0.313	0.129	0.000	Supported
H5	FM → BI	0.097	0.055	0.023	Supported

Note: Goodness of fit: χ^2 = 357.686, df = 153, $p < 0.001$; χ^2/df = 2.33; CFI = 0.969; TLI = 0.961; RMSEA = 0.055; SRMR = 0.055; Coeff. = path coefficient; SE = standard error.

4.3. Moderating Effect in Age and Gender Groups

The next step is to test the moderating effect of age and gender on the relationships between constructs. Table 7 shows the result of measurement invariance test for moderators, age and gender. The results confirmed the measurement invariance between age groups and genders because the difference of chi-square between models with unrestricted versus equal factor loadings (full metric invariance) was insignificant ($p > 0.05$). Table 8a,b shows the test for the moderating effects of age and gender, respectively, on each coefficient. Each row in the tables shows the test result of each research hypothesis. For example, to test the hypothesis H6a in Table 8a, we conducted a Satorra-Bentler chi-square difference test between the model without constraints and the constrained model (the model with a coefficient of PE → BI is fixed for all groups). The result was insignificant (H6a: $\Delta\chi^2(1) = 2.073$, $p > 0.05$), indicating that there is no difference between the constrained model and the model without constraints. Thus, the magnitude of the two path coefficients is insignificantly different in the two models, implying that H6a was not supported. Similarly, the links between EE, SI, and BI were not significantly different between the age groups (H6b: $\Delta\chi^2(1) = 0.440$, $p > 0.05$; H6c: $\Delta\chi^2(1) = 0.715$, $p > 0.05$). Thus, H6b, H6c, and H6d were also not supported. The relationship between HM and BI was significantly different between age groups (H6d: $\Delta\chi^2(1) = 10.10$, $p < 0.01$). However, the result showed that the effect of HM on BI was stronger for the older group than for the younger group. Thus, H6d was also not supported. Only hypothesis H6e was supported (H6e: $\Delta\chi^2(1) = 5.112$, $p < 0.05$), indicating that the effect of FM on BI is greater for younger individuals.

Regarding the moderating effect of gender in Table 8b, the path from EE to BI was significantly different between males and females at the 0.10 level (H7b: $\Delta\chi^2(1) = 3.172$, $p < 0.1$). This indicates that the effect of EE on BI is stronger in the female group than in the male group. Thus, H7b was supported. Also, the link between FM and BI was significantly different between genders (H7e: $\Delta\chi^2(1) = 4.588$, $p < 0.5$), indicating that the effect of FM on BI is stronger for male individuals. Thus, H7e was supported. However, the results have shown that there was no significant difference between genders on the effects of PE, SI, and HM in BI. Thus, H7a, H7c, and H7d were not supported.

Table 7. Measurement invariance test for gender and age groups.

Groups	Model	χ^2 (df)	CFI	TLI	RMSEA	$\Delta\chi^2$ (Δdf)	Results
Age	Non-restricted	860.983 (361)	0.967	0.966	0.056	11.494. (14) $p = 0.647$ (insignificant)	Supported
	Full-metric invariance	878.521 (375)	0.968	0.968	0.055		
Gender	Non-restricted	762.232 (361)	0.972	0.970	0.050	8.242 (14) $p = 0.876$ (insignificant)	Supported
	Full-metric invariance	771.861 (375)	0.973	0.973	0.049		

Table 8. (**a**) Moderating effect test for age group; (**b**) moderating effect test for gender.

(**a**)

Hypotheses	Paths	Young	Old	$\Delta\chi^2$ (Δdf)	p-Value	Results
H6a	PE → BI	0.325 **	0.072	2.073 (1)	0.15	Not supported
H6b	EE → BI	0.275 *	0.168 **	0.440 (1)	0.51	Not supported
H6c	SI → BI	−0.091	0.067	0.715 (1)	0.39	Not supported
H6d	HM → BI	−0.077	0.463 ***	10.10 (1)	0.001	Not supported
H6e	FM → BI	0.369 ***	0.041	9.369 (1)	0.002	Supported

Note: fit indices of age group model: χ^2 = 639.305, df = 306, p < 0.001; χ^2/df = 2.09; CFI = 0.973; TLI = 0.967; RMSEA = 0.051; SRMR = 0.059; * p < 0.1, ** p < 0.05, *** p < 0.01.

(**b**)

Hypotheses	Paths	Male	Female	$\Delta\chi^2$ (Δdf)	p-Value	Results
H7a	PE → BI	0.312 **	0.145	0.912 (1)	0.34	Not supported
H7b	EE → BI	0.028	0.254 **	3.172 (1)	0.07	Supported
H7c	SI → BI	0.144	0.006	0.861 (1)	0.35	Not supported
H7d	HM → BI	0.192	0.341 **	1.854 (1)	0.17	Not supported
H7e	FM → BI	0.212 ***	0.018	4.588 (1)	0.03	Supported

Note: fit indices of age group model: χ^2 = 644.850, df = 306, p < 0.001; χ^2/df = 2.10; CFI = 0.972; TLI = 0.965; RMSEA = 0.052; SRMR = 0.058; * p < 0.1, ** p < 0.05, *** p < 0.01.

5. Discussion

5.1. Implications

There is little doubt that carsharing systems provide benefits in developing sustainable transportation. However, very few studies have covered the topic of the public's acceptance of EC systems in the context of developing countries. The present study, therefore, sets out to fill this gap by adopting the UTAUT model [30]. An important contribution of this study to the literature is that we modified UTAUT by incorporating the influence of hedonic motivation and familiarity with the carsharing concept on the intention to use EC. Four determinants of intention to use EC were found through the result of the modified UTAUT research model, namely performance expectancy, effort expectancy, hedonic motivation, and familiarity with the carsharing concept. Interestingly, hedonic motivation explained the highest amount of variance in behavioral intention, suggesting that one of the most important factors that potential users will consider when deciding to use EC is whether they believe that using EC will be fun and enjoyable. Since EC is a new and innovative transportation mode, this finding is perhaps not surprising. The distinct features of EC design (e.g., visible labeling of the vehicle, electric technology, and flexible services) may attract people's attention in comparison to other transportation modes. This confirms the results obtained in different contexts, such as autonomous vehicles [42] and information technology [63].

Additionally, familiarity with the carsharing concept was identified as a significant antecedent of behavioral intention to use EC. This finding is consistent with several previous studies on e-commerce [59,60]. The strong effect of familiarity indicated that an increase in basic knowledge could result in higher acceptance. Indeed, Wang et al. [24] demonstrated that individuals who know about carsharing are more likely to use it. The initial familiarity is easy to create through education and exposure [59]. Therefore, to enhance the intention to use EC, planners and policymakers should pay more attention to improving individuals' knowledge about EC through effective marketing campaigns such as advertising or organizing training courses prior to using EC systems.

In line with previous studies suggesting that effort expectancy is related to the intention of using new transportation modes [50,51], effort expectancy strongly predicted intention to use EC in the present study. This result is consistent with the findings of an earlier study on corporate carsharing systems [20]. The finding indicates that customer friendliness is an important factor in EC adoption. Therefore, another way to improve the intention to use EC is for vendors to reduce the complexity or uncertainty related to EC service procedures such as the process of searching for and reserving vehicles.

The performance expectancy also has a substantial effect on behavioral intention. This result is similar to that of Fleury et al. [20], indicating that excellent service is one of the most critical factors for accepting EC in the future. As stated by Schaefers [15], convenience was one of the chief motives for using carsharing services. The advantages of carsharing services (e.g., flexible use, reduced ownership responsibility) could make users' lives more comfortable. Thus, a universal way to increase the intention to use EC is for developers to intensify the perception of performance expectancy through emphasizing EC benefits, such as reducing air pollution and traffic congestion, and improving mobility. Meanwhile, developers and the government should also focus on improving the infrastructure of EC systems, which will help to enhance system performance and user enjoyment. There are still constraints on the development of EC systems. While battery technology and charging problems are the primary hindrances to faster adoption of electric vehicles, parking spots are an additional concern for EC systems. Since land-use strategies might deal with the parking problem, support from the government is necessary for a large-scale service. For example, the government can help EC operators to improve EC facilities by providing parking rights in public spaces.

However, contrary to previous studies conducted by Venkatesh et al. [30] and Madigan et al. [42], this study failed to find a significant effect of social influence on behavioral intention to use EC. The rationale for this finding is that EC is new to most respondents and the need to impress others is overshadowed by the need to assess its usefulness after a period of use, as discussed in Venkatesh et al. [30]. In line with many previous studies [20,46,55], our result thus implies that others' opinions are unlikely to be the critical factor in the decision to use EC.

Finally, this study has attempted to validate that the determinants of behavioral intention to use EC varied across different age groups and genders. The results showed the difference in determinants of intention to use EC between groups. For the younger group, all determinants, except social influence and hedonic motivation, were significant, while for the older group, there were only two determinants, effort expectancy and hedonic motivation, that were significant. Also, for the male group, the significant determinants were only performance expectancy and familiarity with the carsharing concept, while for the female group, the significant determinants included effort expectancy and hedonic motivation.

As expected, familiarity with the carsharing concept influences intention to use EC more strongly for the younger group than for the older group. This might be because younger individuals are more likely to engage in new and innovative transportation. As young people are more aware of carsharing systems in general [22], if they have knowledge about the EC service, they are more likely to use it. Moreover, the relationship between familiarity and intention to use was also moderated by gender, and was stronger for men. Therefore, to increase the acceptance of EC among young men, a common way is to increase their knowledge about EC systems.

The effect of effort expectancy on behavioral intention to use EC was stronger for the female group than for the male group. This result is consistent with previous studies on technology acceptance [30,64]. Women have a higher tendency to use the EC system as long as it is easy to use. In other words, feedback from female customers should be taken into account to improve the ease of use of the EC system.

Furthermore, an unexpected and interesting finding of this research is that the effect of hedonic motivation on behavioral intention was significantly higher for older individuals. This finding is contrary to the study of Venkatesh et al. [43], which suggests that hedonic motivation is a stronger determinant of intention for younger individuals. However, hedonic motivation will play a less important role in determining intention to use new technology with increasing experience [43]. Our survey has shown that the percentage of EC users in the younger group was higher than in the older group (28.1% vs. 10.3%), indicating higher experience with EC in the younger group. Therefore, the result could be explained by this bias of the sample. Despite this, the finding suggests that developers need to keep this factor in mind as the system becomes a more common sight. EC should be designed to increase or preserve the enjoyment of users when their experience with EC has increased.

5.2. Limitations and Future Research Directions

An essential strength of this study is that the results focus on psychological factors influencing the public's acceptance of EC systems in the context of a developing country. However, several limitations should be noted. First, this research considered the public's acceptance of EC systems, which is relatively new in the study area. The results rely to a large extent on people's imagination regarding the operation of EC. Lack of information about the frequency of EC usage limited our ability to examine the effects of behavioral intention and behavioral control (e.g., facilitating condition) on actual use. Therefore, other robust approaches should be considered in future research to enhance the findings of this study. For example, actual carsharing behavior and behavioral control (e.g., vehicle size, price) can be obtained from a stated preference survey. A hybrid choice model [95] that combines the latent variables (as in the UTAUT model) and actual choice behavior (as in the discrete choice model) is suggested for future research. Second, respondents were, for the most part, limited to those who are relatively young and well-educated due to the use of a web-based survey. However, previous studies on carsharing have found that these characteristics of potential carsharing customers, including youth and a high level of education, hold true generally [13–15]. Thus, at an early stage of service adoption, it is reasonable to focus on these potential segments to understand the public acceptance of EC. Nevertheless, determining the motives of older EC users (i.e., over 36) will require further research. Since people's perception of EC may change over time, extensive sample surveys and a longitudinal study are needed to thoroughly understand public acceptance. Furthermore, future research is required to understand the impact of other demographic variables on EC acceptance, such as family status or education. Third, the effects of hedonic motivation and familiarity with the carsharing concept on behavioral intention were the main focus on this study that modified the UTAUT model. Other effective factors can be considered to understand the behavioral intention more thoroughly in future research, such as car habits [96] or the usefulness of electric vehicles [50].

6. Conclusions

Despite the limitations mentioned above, this study makes a new contribution to the existing pool of research concerning EC systems. The findings of this research confirmed the validity of the UTAUT model in the context of public acceptance and developing countries. Understanding individuals; acceptance of EC systems brings about significant planning implications and helps us to design procedures for the successful implementation of EC systems in the future. Several suggestions for policy-makers can be made. (1) Improving the quality of EC services is the first and most important step to increase behavioral intention. (2) EC usage can be promoted by increasing the knowledge of travelers about EC's benefits, as well as travelers' awareness of carbon emissions from travel. (3) Support from the government is needed for the efficient development of EC services. (4) Market promotion of EC should take the age and gender of specific target groups into consideration. (5) Different strategies could be integrated within the EC service (e.g., carpooling, integration with the transit system) to increase the effectiveness of EC in reducing car ownership. Meanwhile, the local government should develop policies to control the increase in car ownership (e.g., car use restriction, a vehicle quota system, congestion charging, and low-emission zones). In conclusion, through evaluating the effect of psychological factors on EC acceptance issues in a large city of China, this study might provide guidance for other large cities in developing countries.

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Appendix A

Testing of normality for our data was conducted by estimating the univariate Kurtosis and Skewness. The absolute values of Skewness and Kurtosis were less than 2 and 7, respectively, which are considered acceptable values for the SEM model [97]. Table A1 represents the Skewness and Kurtosis indexes of our data. None of the values exceeded the cutoff values, assuming that the research data approximately follow the normal distribution.

Table A1. Skewness and Kurtosis indexes of the data.

Indicators	Skewness		Kurtosis	
	Coeff.	**Std.**	**Coeff.**	**Std.**
PE1	−0.478	0.117	0.158	0.233
PE2	−0.071	0.117	−0.406	0.233
PE3	0.007	0.117	−0.105	0.233
PE4	−0.241	0.117	−0.030	0.233
EE1	−0.233	0.117	0.010	0.233
EE2	−0.593	0.117	0.472	0.233
EE3	−0.745	0.117	10.355	0.233
EE4	−0.585	0.117	0.634	0.233
SI1	−0.314	0.117	−0.190	0.233
SI2	−0.776	0.117	10.107	0.233
SI3	−0.580	0.117	0.416	0.233
FC1	−0.145	0.117	0.056	0.233
FC2	−0.024	0.117	−0.266	0.233
FC3	−0.273	0.117	0.292	0.233
FC4	−0.270	0.117	−0.256	0.233
HM1	−0.240	0.117	0.146	0.233
HM2	−0.139	0.117	0.619	0.233
HM3	−0.040	0.117	0.417	0.233
BI1	−0.146	0.117	−0.571	0.233
BI2	−0.162	0.117	−0.664	0.233
BI3	−0.275	0.117	−0.378	0.233
BI4	−0.109	0.117	−0.504	0.233
F1	−0.339	0.117	−0.410	0.233
F2	−0.373	0.117	−0.241	0.233
F3	−0.504	0.117	−0.143	0.233
F4	−0.265	0.117	−0.372	0.233

Note: Coeff. = the Skewness and Kurtosis values; Std. = Standard error of Skewness and Kurtosis.

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