

The impact of facilitating conditions on electric vehicle adoption intention in China: An integrated unified theory of acceptance and use of technology model

International Journal of Engineering Business Management
Volume 15: 1–15
© The Author(s) 2023
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/18479790231224715
journals.sagepub.com/home/enb
 Sage

Dingni Wang¹, Mucahit Ozden¹ and Yung Po Tsang²

Abstract

This research aims to explore the influential factors that promote and impede Chinese customers' adoption intention of electric vehicles (EVs). An extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to gauge customers' willingness to adopt EVs. 348 responses and structural equation modelling were employed for analysis. This paper contributes to this research area mainly through two aspects: First of all, it provides more robust evidence of the positive moderating effects on price value since few research studies on it. Secondly, the positive moderating effects of facilitating conditions between perceived risk and adoption intention of EVs were found for the first time, which fills the gap in this research area. Except these, the results also showed that performance expectations, social influence, and price value positively influence EV adoption intention, while perceived risk has a negative impact. Additionally, age and gender were found to significantly moderate adoption intention. These findings offer insights for policymakers to craft more effective policies, ultimately advancing sustainability and accelerating the achievement of long-term carbon neutrality goals.

Keywords

Electric vehicle, adoption intention, unified theory of acceptance and use of technology, structural equation modelling

Date received: 28 October 2023; accepted: 15 December 2023

Introduction

By 2030, the transportation sector is forecasted to be using roughly a fifth of the world's energy resources and produce over a quarter of the world's energy-related carbon emissions.¹ This trend is due to the fact that citizens globally tend to consume fossil fuels to power their automobiles since fossil fuels are both cheap and easily accessible.² The excessive use of fossil fuels does, however, result in substantial greenhouse gas emissions which accelerate global climate change, which is undoubtedly one of humanity's most serious obstacles.² The European Environment Agency posits that road transportation represents the largest proportional contributor to gas emissions and was responsible for 72% of the total greenhouse gas emissions of

both international and domestic transportation in 2019.³ Greenhouse gas emissions from the transportation sector are one of the main hindrances in attaining sustainable economic systems.⁴ Developing transportation with low carbon emissions (e.g., automobile decarbonisation) is both pertinent and crucial to achieving sustainable development

¹Warwick Manufacturing Group, University of Warwick, Coventry, UK

²Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong

Corresponding author:

Mucahit Ozden, Warwick Manufacturing Group, University of Warwick, International Digital Laboratory, Coventry CV4 7AL, UK.
Email: m.ozden.1@warwick.ac.uk



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<https://creativecommons.org/licenses/by-nc/4.0/>) which permits non-commercial use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (<https://us.sagepub.com/en-us/nam/open-access-at-sage>).

goals on a global scale.⁵ In terms of transportation, electric vehicles (EVs) are an ideal substitute for internal combustion engines (ICEs) and are deemed a key technological innovation.^{6,7} EVs draw power from batteries and electric motors which do not generate greenhouse gases as fuel engines do.⁸ EVs are also more energy efficient than ICEs.⁹ Green energy sources (i.e., wind, solar, and hydroelectric energy) can be utilised to charge the batteries of EVs.⁹ The widespread adoption of EVs can therefore significantly decrease greenhouse gas emissions and reduce reliance on fossil fuels.

Since EVs play a key role in reducing environmental damage, various national governments have enacted incentives to support the widespread market adoption of EVs.³ For instance, the South Korean government has implemented incentive policies and built EV-ready infrastructure to boost the total market share of EVs to 6.13% before the year 2025.⁸ Simultaneously, China and the United States have both removed taxation on EV purchases and actively encourage the purchase of EVs by offering financial subsidies to consumers.^{10,11} European nations including Germany, France, and the Netherlands have announced the goal of a total market shift towards EVs by the year 2040. By 2025, Norway plans to have completely transitioned to electric and plug-in hybrid vehicles.¹²

Over recent years, the global demand for EVs has steadily increased. The Global EV Outlook report (see Figure 1) indicates that, by the end of 2022, 26 million EVs had been sold globally – 60% more than in 2021.¹³ Also, EV sales and global stock in 2022 have a similar annual growth rate as in 2021 and 2015–2018 period, demonstrating the robust recovery to the pre-pandemic pace of EV market expansion.¹³ Many companies are presently entering the EV market and developing their own proprietary EV technologies. For example, the Ford Fusion Energy, Renault Zoe, and the Tesla Model S are currently the top products in

the global EV market.¹⁴ With a particular emphasis on light-duty vehicles (LDVs), most producers of EVs are planning to broaden their model ranges in the coming decades.¹³ Projections suggest that the total number of LDVs manufactured will exceed 20 million by 2025 and 40 million by 2030.¹³

China has the largest EV market in the world, particularly in the public transportation industry, where electric buses have mostly replaced oil-fired buses.¹⁵ The number of new EV registrations in China reached 6.9 million in 2022, ranking it first globally for 8 years in a row.¹⁶ In the future of 2030, China plans to achieve about 45% sales shares of EVs across all road transport segments, which to support China's long-term carbon neutrality target.³ However, Chinese customers still have many concerns since EV sales only account for 16% of domestic sales in 2021, which is still quite low.¹³ The reason may include the worse performance of ICVs, such as speed and travel range.¹⁷ Meanwhile, the convenience of charging for EVs is also always doubted for customers.¹⁸ Robust charging conditions can positively and directly increase the perception of buying EVs.¹⁹ Other factors, including government policy, and reasonable price, can also benefit the adoption intention of EVs.¹⁹ Therefore, this study aims to investigate the effects of UTAUT factors with perceived risk, price value and policy incentives on the adoption intention of EVs in China. The quantitative online survey is used to collect the perception of EVs among Chinese customers. After that, 348 responses are analysed by structural equation modelling. In this study, the positive moderating effect of facilitating conditions between perceived risk and adoption intention of EVs is found for the first time and fills the gap in this research field. The rest of the study is structured as follows: literature review and hypothesis development, research design, results, discussion and implications, and conclusion and future research.

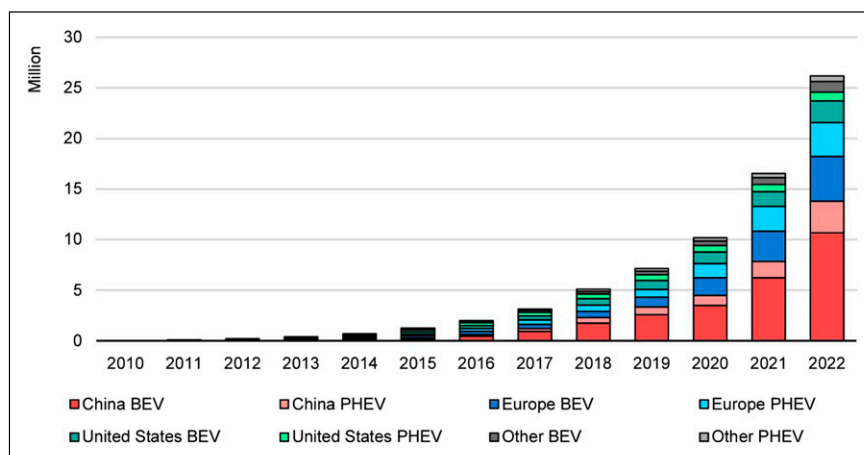


Figure 1. Global EV stock, 2010–2022 (Source: IEA, 2023).

Literature review and hypothesis development

The Unified Theory of Acceptance and Use of Technology (UTAUT) model was developed by Venkatesh et al to evaluate the acceptance of newly-introduced innovations or technologies.²⁰ They integrated eight theories and models, including the Theory of Reason Action (TRA), the Technology acceptance model (TAM), the Motivational model (MM), the Theory of planned behaviour, combined TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT), and finally refined four determinants which directly influence behaviour and behavioural intention, named social influence, effort expectancy, facilitating conditions, and performance expectancy.²⁰ This paper chose to establish the research model based on the UTAUT model rather than the Technology Acceptance Model (TAM) which was created by Davis and Bagozzi²¹ and also broadly used due to the following reasons: (i) In the aspect of validity, the UTAUT performed significantly better than each of the eight individual models with a 70% variance toward the intention, but the TAM typically accounts for about 40%.^{20–22} (ii) The TAM neglects the effects of group, culture and society since a person acting individually is not the best way to describe most human behaviour.^{23,24} This point of view is also supported by Zhang et al., who extended TAM to investigate the acceptance of automation vehicles for 647 Chinese drivers and found social influence contributed the most compared to other constructs.²⁵ However, the UTAUT model compensates for the lack of social influencing factors in the TAM. (iii) Many articles also have proved the advantages of the UTAUT compared with the TAM. For example, Ling et al chose to apply the UTAUT model to find the determinants of computer usage after comparing these two models through reliability, model, measures, validity and focus.²⁶ Rejali et al applied the TAM, UTAUT and TAM to assess a priori acceptance of fully automated vehicles.²⁷ They found the UTAUT may be the best-performing model for practical purposes (i.e. focusing on function, efficiency and usefulness) although the model is relatively complex.^{27,28}

Furthermore, other researchers have studied customers' behavioural intentions regarding EVs using this theory, concluding that the model's predictive accuracy can be greatly enhanced by including more contextual variables.^{29,30} For instance, Khazaei³¹ studied intentions around EV adoption by expanding the UTAUT model to include the variables of price value and personal innovation. Abbasi et al extended the UTAUT model using an additional variable, namely, perceived environmental knowledge, to evaluate EV purchasing intention.³² Jain, Bhaskar and Jain investigated the moderating effects of the UTAUT model on various governments' levels of environmental awareness.³³

Khazaei and Tareq also studied the moderating effect of the UTAUT model of driving experience for personal innovation in the acceptance of EVs.³⁴ Based on these previous studies, this paper proposes a research model based on the UTAUT model expanded with three added variables, namely, price value, perceived risk, and policy incentives, to evaluate the way that consumers currently perceive EVs.

Perceived risk

Dunn et al defined perceived risk as consumers' expected negative utility with purchasing a particular product or service.³⁵ In this paper, 'perceived risk' constitutes consumers' expectations regarding the negative utility of using EVs.³⁵ Wang et al posited that perceived risk associated with EVs is categorizable according to five criteria, namely, time risk, economic risk, performance risk, psychological risk, and physical risk. Doubts around the effective functioning of EVs constitute 'performance risk'.³⁶ The performance metrics of EVs (i.e., acceleration speed, travel range, and charging methods) are lower overall compared to ICVs.^{2,17} Consumers may need to spend more time and effort locating charging stations and charging their vehicles since EV charging stations are still moderately scarce.^{11,37} Time risk is therefore a significant factor to be taken into consideration. Safety and reliability problems (including physical risk) may exist due to the relative immaturity of EV technology.^{38,39} Financial risk results from the high prices of purchasing EVs and replacing their batteries which increases consumers' total expenses.^{40,41}

Based on the above discussion, this paper's first hypothesis is as follows:

H1: Perceived risk negatively affects customers' adoption intention of EVs.

Effort expectancy

'Expectation of effort' is constituted by the level of difficulty or ease related to the utilisation of a given product or system.²⁰ This explanation aligns with 'perceived ease of use,' i.e., the extent to which people can utilise a given technology without an excessive amount of effort (Davis, 1989). In this paper, 'expectation of effort' refers to 'the perceived amount of effort people need to exert when using an EV'.⁴² The operation of EVs is different compared to that of ICVs (e.g., maintenance and battery replacements). The expectation of effort is assumed to positively influence consumers' intention to use EVs.⁴³ A study conducted by Abbasi et al showed that EV purchasing intention is significantly influenced by consumers' expectation of effort and that using EVs requires less effort than using ICVs.³² This notion is reinforced by a study from Gunawan et al which suggests that people who believe that it is easy to

acquire the skill of driving an EV tend to perceive EVs in a more positive light.⁴⁴ Zhou et al showed that Chinese taxi drivers are concerned about the degree of ease or difficulty of using EVs and whether they would need to acquire new driving skills to be able to operate EV taxis.⁴³ On the other hand, a study conducted by Jain, Bhaskar and Jain suggested that, among Indian people, the expectation of effort did not affect their EV purchasing intention.³³

Therefore, it is proposed that:

H2: Effort expectancy positively affects customers' adoption intention of EVs.

Social influence

Social influence is defined as "the degree to which an individual perceives that it is important for others to believe he or she should use the new system".²⁰ This phenomenon has also been called 'the neighbourhood effect'.⁴⁵ Numerous studies have shown that other people, (i.e., friends, work colleagues, and relatives) affect a person's decision-making process. In this paper, 'social influence' refers to 'the extent to which other people believe that a given consumer should adopt EVs'.⁴⁶ The beliefs of other people have been shown to positively influence consumers' intention to adopt EVs. Zhang et al showed, for instance, that the cost of an EV which an individual finds agreeable is influenced by the views of their friends.⁴⁷ Research conducted by Abbasi et al indicated that Malaysian consumers' EV adoption intentions are significantly influenced by various social factors.³²

Based on the above discussion, we propose the following hypothesis:

H3: Social influence positively affects customers' adoption intention of EVs.

Performance expectancy

The definition of 'expectation of performance' is 'the degree to which a person believes that using a certain product would help them to realize performance gains'.²⁰ People who believe that technology benefits them tend to be more positively predisposed toward using new technological products.¹ In this paper, 'expectation of performance' refers to 'an individual's perceived benefit in terms of the performance of EVs'.^{7,20} Jain, Baskar and Jain showed that expectation of performance has a significant influence on the adoption intention of EVs, whereas limited travelling range is commonly seen as its primary drawback.³³ These findings were supported by a study conducted by Zhang et al which demonstrated that performance metrics more significantly influence consumers' confidence and value perception of EVs than any other factor.⁷ Bhat, Verma and Verma researched the correlation between the expectation of

performance and anxiety about EV technology among consumers.⁴⁸ They showed consumers' anxiety and apprehensions around EVs tend to be lower when they have a more positive opinion about the performance of EVs.⁴⁸

Therefore, the following hypothesis is presented:

H4: Performance expectancy positively affects customers' adoption intention of EVs.

Price value

Price value refers to consumers' expectations around cost management.⁴⁹ It can also be defined as the cost-benefit relationship that broadly affects people's adoption intention of a novel technology.⁴² If the cumulative benefits of a service or product outweigh a consumer's expectations, it is deemed to have a high price value.⁵⁰ In this paper, 'value' refers to the cumulative benefit that EVs deliver to consumers. EVs are charged using electricity which is more cost-effective than purchasing fuel for ICVs.⁵¹ Another key benefit of EVs is lower maintenance costs compared to ICVs.⁵¹ Gunawan et al suggested that consumers who perceive a correlation between the price and quality of EVs are more inclined to accept EVs and show a greater interest in using them.⁴⁴ Similarly, Han et al reported the majority of Chinese consumers in Hefei province would be more likely to purchase EVs if they were competitively priced compared to conventional ICVs.⁵² If the advantages of a service or product surpass a consumer's expectations, it is deemed to have a high price value.⁵⁰

Based on the above point of view, the following hypothesis is presented:

H5: Price value positively affects customers' adoption intention of EVs.

Policy incentives

Multiple papers have reported that consumers' willingness to adopt EVs is enhanced by policy incentives. As an example, Li et al showed that people are more likely to buy EVs when tax reductions and subsidies are offered to them.² Similarly, Wang et al reported that consumers' intentions to purchase EVs are greatly increased as a result of preferential tax policies.¹¹ Nonetheless, few studies have investigated policy incentives' moderating effect. Jain, Bhaskar and Jain showed that the correlation between perceived risk and consumers' intention to adopt EVs is moderated by government support.³³ Kim et al reported that financial incentives only exhibit a moderating effect between adoption intention and the perceived value of EVs.⁵³ This paper aims to investigate the moderating effect of policy incentives on the adoption intention and price value of EVs.

The following hypothesis is therefore put forward:

H6: The relationship between adoption intention and price value of EVs is moderated by policy incentives.

Facilitating conditions

‘Facilitating conditions’ can be defined as ‘the degree to which a person perceives that an underlying technical or organisational infrastructure exists to facilitate the utilisation of a given product or system’.²⁰ In this paper, ‘facilitating conditions’ will refer to consumers’ beliefs regarding the available support and resources to facilitate the utilisation of EVs, including the infrastructural distribution, charging conditions and the total amount of operational charging stations.^{8,20,54–56} Limited travelling range is commonly seen as the primary drawback of EVs.³³ Also, Chinese consumers are relatively concerned about the availability of charging stations, they may need to put more effort to find charging stations due to the scarce amount.^{11,18} Since performance and time risk of perceived risk are caused mainly due to the fact of charging concerns, the moderating effect of facilitating conditions is worth studying. However, no study has investigated the moderating role of facilitating conditions between perceived risk and consumers’ EV adoption intention.

Therefore, this study presents the hypothesis as follows:

H7: Facilitating conditions moderate the relationship between perceived risk and adoption intention of EVs.

Demographic characteristics

Gross monthly income, education level, age, and gender are the control variables that moderate the model used in this study. Previous studies have shown that different age and gender groups perceive EVs differently. For example, She et al demonstrated that people’s willingness to adopt EVs increases with age and that middle-aged and elderly people tend to be more inclined to purchase EVs.¹⁸ Lashari, KO and Jang showed that, compared to females, males tend to be more attracted to EVs.⁵⁷ They also showed that, due to its high cost, younger age groups tended to hold a more negative view in terms of their intention to adopt EVs. In terms of education and income level, one study reported that individuals with higher education and income levels are more likely to adopt and purchase EVs.⁵⁸

Based on the above discussion, this paper hypothesises the following:

H8: Participants’ age moderates the relationship among the variables in the research model.

H9: Participants’ gender moderates the relationship among the variables in the research model.

H10: Participants’ monthly income moderates the relationship among the variables in the research model.

H11: Participants’ educational level moderates the relationship among the variables in the research model.

The research model resulting from these hypotheses is developed in [Figure 2](#)

Research design

Study measures

Chinese consumers’ intention to adopt EVs was studied using a quantitative online survey. The questionnaire consisted of a consent form and two main sections. The participants’ demographic criteria, including age, gender, monthly income, and education level were established in the first section. The demographic criteria were determined based on the existing research literature on the perception of EVs among Chinese customers. The second section of the questionnaire collected data on the constructs by way of adapting pre-existing measurement methods using the seven-point Likert scale. The questionnaire participants responded with levels 1 (‘strongly disagree’) through 7 (‘strongly agree’) to indicate their level of agreement or disagreement (see [Appendix A](#)). The questions were presented to the participants in a random order. An ‘attention check’ question was also included, requiring the participants to choose a specific answer. Questionnaires with incorrect ‘attention check’ answers were excluded from the dataset.

Research population and sample

Four hundred and seventy-six (476) cases were taken in total to satisfy this condition. It took 15 days to collect the response, starting from 6th June to 21st June 2022. After removing cases which clearly showed false answers (e.g., excessive repetitiveness) or which were completed with a response time of fewer than 150 s, 348 authentic responses remained to be statistically analysed. The authentic rate of response for the questionnaire is therefore 73.1%. The sample size met the following prerequisites of conducting SEM techniques: (i) Using the SEM technique, the study’s sample size should exceed fivefold the total number of questions.⁵⁹ Eight constructs were considered in this study, each of which had four observed variables to measure. The sample size should therefore 160 or greater (5*32 questions = 160 respondents). (ii) The sample size should fall within the range of 200 – 400.^{60,61} (iii) 10 to 15 cases per item are suggested to run the multivariate analyses such as structural equation modelling (SEM) (10 cases*32 items = 320).^{62,63} The quantity of 348 valid responses is also in this range. In addition, the gender-based frequency distribution is quite balanced, with 52.6% female and 47.4% male participants.

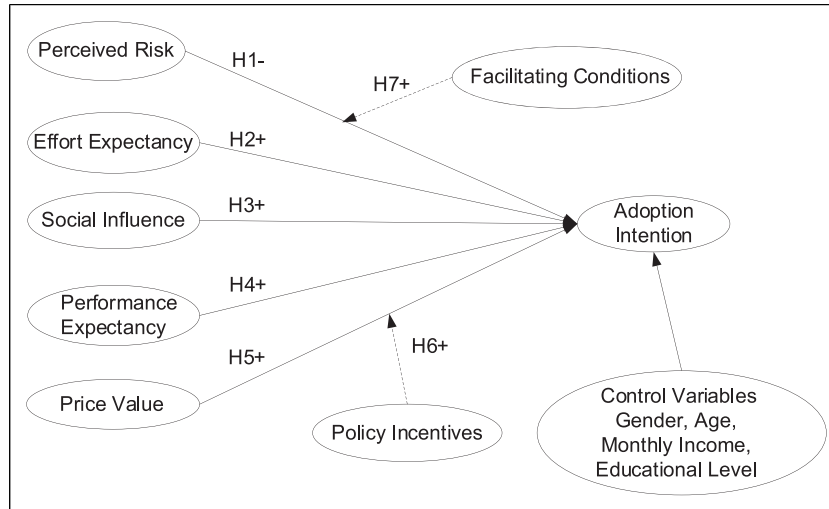


Figure 2. Research model.

Pretesting

Before the questionnaires were officially distributed, preliminary surveys were carried out with 20 participants to confirm that the questions were easily comprehensible and representative of the variables we sought to measure. 3 questions were slightly altered to improve their comprehensibility according to the feedback we received. First of all, numbers and service radius of public charging spots and stations were added as notes to better explain the availability of public infrastructure for EVs. Office building was added as well as the example of the workplace to test the convenience of public infrastructure. And then, the example of financial losses, including repair and battery costs, was also shown on the survey to remind participants. The pretest participants' duration to complete the questionnaire was recorded during the pretesting phase, with the fastest time being 150 s. Questionnaires that were completed faster than 150 s were therefore regarded as invalid, to help ensure the collection of quality data.

Data analysis

Using Amos 27, confirmatory factor analysis (CFA) was carried out to evaluate the data's validity, reliability, and goodness of fit. Cronbach's alpha, composite reliability and average value were tested to promise the construct reliability. After that, factor loadings and the square root of AVE were calculated to determine the convergent and discriminant validity. Based on the above value of data and its criteria, the measurement model was analysed to validate whether the hypotheses could be tested with an adequate degree of reliability. To minimize multicollinearity between the variables, the variance inflation factors (VIFs) were calculated. Finally, regarding the structural model, the hypotheses testing was conducted.

Results

Demographic data

Regarding the participants' age, the largest age group was between 18 – 25 years old (30.5%), the second largest age group was between 36 – 50 years old (26.4%), the third largest age group was 50 years old (23%), and the smallest age group was between 26 – 35 years old (20.1%), as shown below in Table 1. Regarding the participants' education level, the largest group held either a bachelor's degree or an associate's degree (60.6%), the second largest group held a doctoral degree or a master's degree (30.7%), and the smallest group were still enrolled in senior high school or below (8.6%). Regarding the participants' monthly income, 9.2% had a monthly income of over 12,000 CNY, 25.3% had a monthly income between 8000 – 12,000 CNY, 33% had a monthly income between 4000 – 8000 CNY, and 32.5% had a monthly income of less than 4000 CNY.

Measurement model testing

The composite reliability and Cronbach's alpha values were calculated to ensure the constructs' reliability. As indicated by Hair et al and Straub, these values should exceed 0.7.^{62,64} Using average variance extracted (AVE) and factor loadings, the convergent validity was calculated, all of which should exceed 0.5 as indicated by Hair et al and Fornell and Larcker.^{62,65} Based on the prerequisites, a data elimination process was enacted to ensure that the standard values given above were met. Table 2 shows the results of this elimination process. Based on the recommended values put forward by Hu and Bentler,⁶⁶ the revised data showed an increased goodness-of-fit for the measurement model ($X^2/df = 1.307 \rightarrow 1.339$; $RMSEA = 0.03 \rightarrow 0.031$; $AGFI = 0.894$).

Table 1. Demographics of respondents ($N = 348$).

Demographic features	Categories	Frequency	Percent	Cumulative Percent
Gender	Male	165	47.4	47.4
	Female	183	52.6	100.0
	Others	0	0.0	0.0
Age	18–25 years old	106	30.5	30.5
	26–35 years old	70	20.1	50.6
	36–50 years old	92	26.4	77.0
	Over 50 years old	80	23.0	100.0
Educational level	Senior high school or below	30	8.6	8.6
	Associate degree/Bachelor's degree	211	60.6	69.3
	Master's degree/PhD degree	107	30.7	100.0
Monthly income	Less than 4000 RMB	113	32.5	32.5
	4000–8000 RMB	115	33.0	65.5
	8,000–12,000 RMB	88	25.3	90.8
	Over 12000 RMB	32	9.2	100.0

→ 0.902; CFI = 0.975 → 0.977; IFI = 0.975 → 0.977; TLI = 0.971 → 0.972). As the final step of the CFA, discriminant validity was determined. On the diagonal of each construct, the square root of AVE was greater than its correlations with other constructs (see Table 3), indicating an acceptable degree of discriminant validity.⁶⁵ To test for multicollinearity, variance inflation factors (VIFs) were calculated. For each construct, the value of tolerance was >0.1 and the VIF values were all <1.8, which is significantly below the threshold of 3.⁶² Based on these calculations, it was determined that there was no multicollinearity among the variables.

Structural model and hypotheses testing

The structural model fit test was designed according to the criteria recommended by Hu and Bentler.⁶⁶ Table 4 indicates that the values of fit indices all fall within the recommended thresholds, therefore demonstrating that the model fit test was correct. Next, the hypotheses testing could be carried out.

The analysis result shows a Coefficient of Determination (R^2) value of 0.68, indicating that 68% of consumers' EV adoption intention is explainable by social influences, price value, performance expectancy, and perceived risk. The results of the path analysis are shown in Table 5. Consumers' adoption intention was negatively influenced by perceived risk (H1; $\beta = -0.154$, $p = .001$), thus confirming hypothesis 1. Effort expectancy did not have any influence on consumers' adoption intention (H2; $\beta = 0.029$, $p = .548$), thus rejecting hypothesis 2. Consumer's intention to adopt EVs were all significantly influenced by price value (H5; $\beta = 0.231$, $p = .001$), performance expectations (H4; $\beta = 0.286$, $p < .001$), and social influence (H3; $\beta = 0.384$, $p < .001$), thus confirming hypotheses 2, 3 and 4.

The moderating roles of facilitating conditions and policy incentives were respectively proven. The relationship between consumers' EV adoption intention and price value was greatly influenced by policy incentives (H6; $\beta = 0.099$, $p = .038$), as demonstrated in Figure 3. Based on this result, it can be concluded that reasonable prices combined with governmental policy support could improve consumers' view of EVs, thus confirming hypothesis 6.

The relationship between consumers' EV adoption intention and perceived risk was positively influenced by the moderating effects of facilitating conditions (H7; $\beta = 0.221$, $p = .003$), thus confirming hypothesis 7. The negative effect of perceived risk on adoption intention is reduced by facilitating conditions, as shown in Figure 4. In conclusion, the expected negative utility that consumers associate with EVs is reduced by facilitating conditions.

Multigroup structural equation modelling was conducted to assess the moderating effects of each control variable along each path. To this end, the structural weight of each path was constrained before being compared with unconstrained models. According to Table 6, the relationship between consumers' EV adoption intention and the different constructs was greatly influenced by age ($p < .001$) and gender ($p = .045$). However, gender showed a comparatively trivial influence. EV adoption intention was not influenced by the other two control variables (i.e., educational level and monthly economic income).

We further evaluated the influence of gender on each main path. Adoption intention was positively influenced by social factors for both women ($\beta = 0.401$, $p < .001$) and men ($\beta = 0.43$, $p < .001$), as shown in Table 7. Notably, men ($\beta = 0.27$, $p = .017$) showed less priority in the performance of EVs than women ($\beta = 0.299$, $p = .003$). Although the adoption intention of EVs was not influenced by price value for women ($\beta = 0.14$, $p = .156$), it was for men ($\beta = 0.297$,

Table 2. Reliability and convergent validity.

Variables	Factor loadings	AVE	CR	Cronbach's Alpha
Effort Expectancy				
EE1	0.787	0.568	0.798	0.797
EE2	0.738			
EE4	0.735			
Performance expectancy				
PE2	0.771	0.542	0.779	0.774
PE3	0.777			
PE4	0.654			
Facilitating conditions				
FC1	0.792	0.562	0.837	0.834
FC2	0.729			
FC3	0.768			
FC4	0.707			
Price value				
PV1	0.790	0.587	0.810	0.821
PV2	0.720			
PV4	0.787			
Policy incentives				
PI1	0.779	0.560	0.792	0.790
PI2	0.771			
PI4	0.691			
Perceived risk				
PR1	0.721	0.535	0.775	0.771
PR3	0.668			
PR4	0.800			
Social influence				
SI1	0.791	0.632	0.837	0.837
SI2	0.760			
SI3	0.832			
Adoption intention				
AI1	0.717	0.599	0.856	0.855
AI2	0.853			
AI3	0.795			
AI4	0.723			

Table 3. Discriminant validity.

	AI	PR	SI	PI	PV	FC	PE	EE
AI	0.754							
PR	0.314	0.736						
SI	0.707	0.167	0.750					
PI	0.477	0.087	0.581	0.766				
PV	0.666	0.169	0.564	0.401	0.748			
FC	0.588	0.152	0.392	0.247	0.657	0.795		
PE	0.690	0.194	0.559	0.512	0.641	0.610	0.732	
EE	0.274	0.049	0.211	0.525	0.255	0.231	0.343	0.774

Notes: AI: Adoption Intention; PR: Perceived Risk; SI: Social Influence; PI: Policy Incentives; PV: Perceived Value; FC: Facilitating Conditions; PE: Performance Expectancy; EE: Effort Expectancy.

Table 4. Results of model fit.

Fit Indices	Results
χ^2/df	1.249
RMSEA	0.027
GFI	0.952
AGFI	0.934
CFI	0.988
IFI	0.988
TLI	0.985

$p = .003$). When utilising EVs, women were concerned about potential risk ($\beta = -0.1947$, $p = .005$). Meanwhile, men's EV adoption intention was not influenced by perceived risk ($\beta = -0.1$, $p = .118$).

Table 8 shows the multigroup test results for all the participants' age groups. The age groups of 18 – 25 years old ($\beta = 0.496$, $p < .001$), 26 – 35 years old ($\beta = 0.382$, $p = .001$), and >50 years old ($\beta = 0.618$, $p = .003$) were all influenced by social factors, but not the age group between 36 – 50 years old, who placed more priority on reasonable pricing ($\beta = 0.494$, $p = .001$). The factors that most influenced the adoption intention of the participants in the age group between 26 – 35 years were EV performance ($\beta = 0.329$, $p = .011$) and potential risk ($\beta = -0.402$, $p = .003$).

Discussion and implications

Theoretical implications

This paper investigates the adoption intention of EVs based on the extended UTAUT model with policy incentives, perceived risk and price value in the Chinese context. The results found social influence, performance expectancy and price value all have positive effects on adoption intention, which is in line with the existing research.^{7,33,44,52,67,68} At the same time, perceived risk is proven to have negative effects which is also consistent with studies written by Schuitema et al, Wang et al and Vafaei-Zadeh et al.^{36,37,50} Furthermore, this study also contributes to the moderation effects on the relationship between price value and adoption intention towards EVs, which was studied little by previous researchers.⁴¹ Lastly, since no paper suggests the moderating role of facilitating conditions between perceived risk and adoption intention, this study tries to fill this gap. Therefore, this study enriches the current study by reconfirming the proven factors and proposing the moderation effects of policy incentives and facilitating conditions.

Practical implications

Construction of charging infrastructures. As a main priority, obstacles to charging infrastructure must be overcome. The Chinese government should therefore undertake the

Table 5. Summary of hypotheses results.

Hypotheses	Construct	Standardized estimate	p-value
H1 (supported)	Perceived risk	−0.154	.001
H2 (unsupported)	Effort expectancy	0.029	.548
H3 (supported)	Social influence	0.384	<.001
H4 (supported)	Performance expectancy	0.286	<.001
H5 (supported)	Price value	0.231	.001
H6 (supported)	Policy incentives	0.099	.038
H7 (supported)	Facilitating conditions	0.221	.003

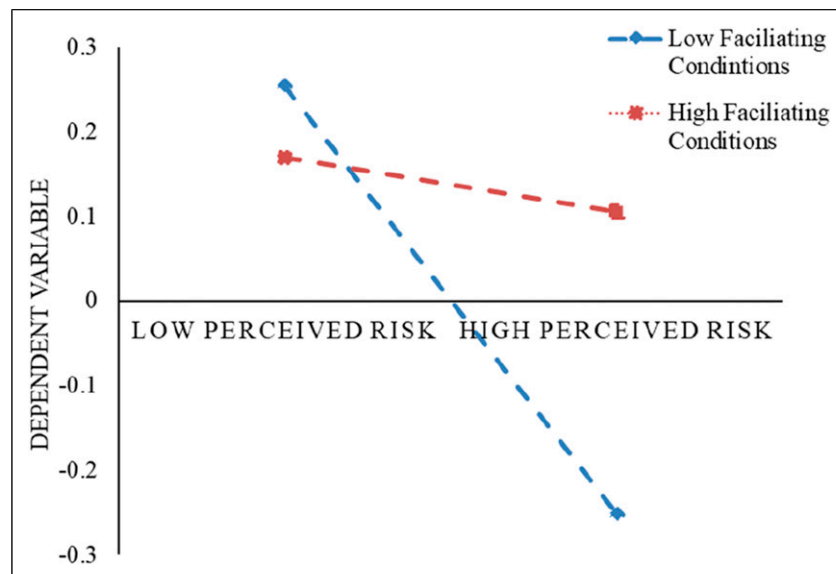
**Figure 3.** Moderating effect of policy incentives.**Figure 4.** Moderating effect of policy incentives.

Table 6. Summary of hypotheses results for control variables.

Hypotheses	Control variables	DF	CMIN	p-value	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
H8 (supported)	Age	15	39.756	.000	0.011	0.013	0.006	0.008
H9 (supported)	Gender	5	11.365	.045	0.004	0.004	0.002	0.002
H10 (unsupported)	Monthly income	15	7.149	.953	0.002	0.002	−0.004	−0.005
H11 (unsupported)	Educational level	10	18.068	.054	0.005	0.006	0.001	0.001

Note: *** $p < .001$; ** $p < .01$; * $p < .05$.

Table 7. The Multigroup SEM results of gender.

Regression Weights	Male		Female	
	Standardized estimate	p	Standardized estimate	p
Adoption intention <--- Social influence	0.43	***	0.401	***
Adoption Intention <--- Effort expectancy	−0.143	.055	0.14	.035
Adoption Intention <--- Performance expectancy	0.27	.017*	0.299	.003**
Adoption Intention <--- Price value	0.297	.003**	0.14	.156
Adoption Intention <--- Perceived risk	−0.1	.118	−0.194	.005**

Note: *** $p < .001$; ** $p < .01$; * $p < .05$.

Table 8. The Multigroup SEM results of age.

Regression Weights	18–25 years old		26–35 years old		36–50 years old		Over 50 years old	
	Standardized estimate	p	Standardized estimate	p	Standardized estimate	p	Standardized estimate	p
Adoption Intention <--- Social Influence	0.496	***	0.382	.001**	0.222	.148	0.618	.003**
Adoption Intention <--- Effort	0.007	.938	−0.089	.467	0.06	.505	0.564	.006
Adoption Intention <--- Performance_ Expectancy	0.173	.251	0.329	.011*	0.322	.04	0.335	.156
Adoption Intention <--- Price value	0.189	.091	0.207	.093	0.494	.001**	−0.475	.14
Adoption Intention <--- Perceived risk	−0.201	.061	−0.402	.003**	0.013	.855	−0.161	.152

Note: *** $p < .001$; ** $p < .01$; * $p < .05$.

extensive construction of new charging stations, making considerations for the total amount of charging stations, as well as their locations and distribution patterns. This would enable citizens to recharge their EVs in a timely manner, regardless of whether they are travelling in rural or urban regions, or on highways. The government could also incentivise different types of merchants and businesses (i.e., gas stations, stores, hotels, and restaurants) to invest in building new charging stations on or near their business premises. This would ensure adequate availability of charging infrastructure for EVs. To guarantee the correct operation of these new charging stations, new managerial policies are also necessary.

Increasing public awareness of electric vehicles. It is also necessary to improve potential buyers' understanding of EVs. To this end, several important features should be taken into account. EV producers must educate consumers about the advantages of EVs since potential buyers will evaluate whether the potential value offered to them by EVs would justify their price. For instance, EVs have lower long-term operating costs than ICVs as a result of factors such as lower fuel costs and maintenance costs. Nonetheless, consumers tend to ignore this fact and are overly concerned that the cost of purchasing an EV is comparatively high. To improve consumers' perceived value of EVs, their long-term cost-saving benefits should therefore be more actively promoted. On the other hand,

consumers should also be more informed about the performance of EVs. To this end, EV producers could offer costless test drives to the general public which would help to alleviate consumers' concerns about the performance of EVs. Once consumers are more informed about the advantages of EVs, their levels of perceived risk and other misconceptions will be greatly reduced. At the same time, this would enhance consumers' confidence and positive views on the value of EVs.

Focusing more on financial incentives. This paper has demonstrated that the effect of price value on consumers' intention to adopt EVs is positively enhanced by policy incentives. Policy implications can thus be deemed to be pivotal in this discussion. Governments should develop broader incentive policies with a specific emphasis on economic incentives for end consumers (e.g., loan limits, subsidies on EV purchases, and tax exemption policies) should be appropriately designed, enacted, and revised. The government could also collaborate with EV producers to develop effective economic incentive policies and contribute towards innovative new cooperative business models.

Improving LIBs' capacity and end-of-life management. Producers of EVs should fund research and development in enhancing EV technology to improve their performance metrics. For instance, developing LIBs with higher capacities would alleviate consumers' concerns about EVs' limited travel range and long charging duration. This type of innovation would improve the expectation of performance and perceived risk among consumers. In terms of reverse logistics, LIB producers should introduce incentive programmes to urge consumers to promptly return their end-of-life LIBs and consider offering a free battery collection service to customers.⁶⁹ Governments should also actively increase environmental issues awareness among the public and promote the importance of recycling end-of-life batteries among EV purchasers. This would help curb the high demand for LIBs, and effectively reduce costs to EV producers through recycling, reusing, and/or re-manufacturing processes.

Taking priority in targeting groups. This paper showed that women are generally more interested in EVs than men. The significance of women's adoption intention towards EVs should not be disregarded. Consumers in younger age groups are also more interested in EVs than any other age group.⁷⁰ Hence, EV producers should develop targeted strategies to appeal to these target groups in particular. Young people's and women's views regarding EVs should constantly be analysed to help guide innovation in the EV market.

Conclusion and future research

This paper aims to evaluate consumers' perceptions of EVs to identify ways in which EV supply chains may be improved. An extended UTAUT model which integrates policy incentives, price value, and perceived risk was quantitatively analysed using the SEM approach. The analysis results indicate that social influences, perceived risks, price value, and expectation of performance all greatly influence consumers' EV adoption intention. However, the expectation of effort had no significant influence on EV perception among consumers. In particular, the positive moderating effects of policy incentives on price value were reconfirmed to provide more robust evidence since few research studies on it. In addition, the positive moderating effects of facilitating conditions between perceived risk and adoption intention of EVs were found for the first time in this study, which fills the gap in this area. Consumers' demographic profiles were also taken into consideration, including age, gender, educational level, and gross monthly income, as control variables. Gender and age were proven to have significant moderating effects on EVs' adoption intention. This paper has therefore added to the existing research literature on the subject of optimising EV supply chains and research involving the use of the UTAUT model extended with added variables. The paper also holds significance for both policymakers and producers of EVs and may help them to optimise the EV supply chain by designing financial incentive policies, building sufficient charging infrastructure, improving the management of end-of-life LIBs, and creating more awareness of EVs among consumers.

This paper has certain limitations. First, since many other variables may influence consumers' perception of EVs, the empirical model used in the analysis should be further extended. For instance, future studies could investigate additional factors such as consumers' knowledge of EVs and environmental awareness. Second, since this paper also included a relatively small number of participants from higher-income groups and lower-education groups, the EV adoption intention of these two groups may have been disregarded. To compensate for this limitation, future studies should explore the influences of monthly income and educational level more comprehensively by including more participants. Other demographic variables (e.g., geographical location, occupation, driving experience) could also be included. With a sufficiently large amount of sampling data, consumers who have previously purchased and used EVs and consumers who are still contemplating purchasing an EV could be separated into two distinct groups for further research.

Furthermore, consumers' understanding and views of EVs may vary based on different brands of EVs since they have different performance metrics, features, and prices. As

a result of this, this paper may not comprehensively represent the influences of price value and performance expectancy on consumers' EV adoption intention. Future researchers should therefore attempt to minimise potential bias among study participants by detailing the specific price points and performance metrics of EVs when designing questionnaires.

Finally, local municipalities have different policies for promoting EVs which may differ from the central Chinese government's overarching policies. The influence of the enactment of different policies may differ based on geographical locations and local market conditions. Future research should gather more conclusive evidence from various Chinese provinces and cities since local policies and consumers' perceptions regarding EVs may vary across different regions.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Mucahit Ozden  <https://orcid.org/0000-0001-5220-4230>

References

1. Wang X, Wong YD, Li KX, et al. This is not me! Technology-identity concerns in consumers' acceptance of autonomous vehicle technology. *Transport Res F Traffic Psychol Behav* 2020 Oct; 74: 345–360.
2. Li W, Long R, Chen H, et al. Effects of personal carbon trading on the decision to adopt battery electric vehicles: analysis based on a choice experiment in Jiangsu, China. *Appl Energy* 2018 Jan; 209: 478–488.
3. *Global EV Outlook 2021*. International Energy Agency, 2021, p. 101.
4. Ajanovic A. The future of electric vehicles: prospects and impediments. *WIREs Energy Environ* 2015; 4(6): 521–536.
5. Bobeth S and Kastner I. Buying an electric car: a rational choice or a norm-directed behavior? *Transport Res F Traffic Psychol Behav* 2020 Aug; 73: 236–258.
6. He X, Zhan W and Hu Y. Consumer purchase intention of electric vehicles in China: the roles of perception and personality. *J Clean Prod* 2018 Dec; 204: 1060–1069.
7. Zhang W, Wang S, Wan L, et al. Information perspective for understanding consumers' perceptions of electric vehicles and adoption intentions. *Transport Res Transport Environ* 2022 Jan; 102: 103157.
8. Byun H, Shin J and Lee CY. Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. *Energy* 2018 Feb; 144: 312–321.
9. Li W, Long R, Chen H, et al. A review of factors influencing consumer intentions to adopt battery electric vehicles. *Renew Sustain Energy Rev* 2017 Oct; 78: 318–328.
10. Dumortier J, Siddiki S, Carley S, et al. Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle. *Transport Res Pol Pract* 2015 Feb; 72: 71–86.
11. Wang S, Li J and Zhao D. The impact of policy measures on consumer intention to adopt electric vehicles: evidence from China. *Transport Res Pol Pract* 2017 Nov 1; 105: 14–26.
12. Crabtree G. The coming electric vehicle transformation. *Science* 2019 Oct 25; 366(6464): 422–424.
13. International Energy Agency. *Global EV Outlook 2023: catching up with climate ambitions*. [Internet]. Paris, France: OECD; 2023 [cited 2023 Dec 9]. (Global EV Outlook). Available from: https://www.oecd-ilibrary.org/energy/global-ev-outlook-2023_cbe724e8-en
14. Cecere G, Corrocher N and Guerzoni M. Price or performance? A probabilistic choice analysis of the intention to buy electric vehicles in European countries. *Energy Pol* 2018 Jul; 118: 19–32.
15. Shi L, Wu R and Lin B. Where will go for electric vehicles in China after the government subsidy incentives are abolished? A controversial consumer perspective. *Energy* 2023 Jan; 262: 125423.
16. Tang Y, Zhang Q, Liu B, et al. What influences residents' intention to participate in the electric vehicle battery recycling? Evidence from China. *Energy* 2023 Aug 1; 276: 127563.
17. Higuera-Castillo E, Guillén A, Herrera LJ, et al. Adoption of electric vehicles: which factors are really important? *Int J Sustain Transp* 2021 Aug 2; 15(10): 799–813.
18. She ZY, Sun Q, Ma JJ, et al. What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. *Transport Pol* 2017 May; 56: 29–40.
19. Wu W and Lin B. Benefits of electric vehicles integrating into power grid. *Energy* 2021 Jun 1; 224: 120108.
20. Venkatesh V, Morris MG, Davis GB, et al. User acceptance of information technology: toward a unified view. *MIS Q* 2003; 27(3): 425–478.
21. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q* 1989 Sep; 13(3): 319.
22. Hasani T, Rezaei D, Levallet N, et al. Privacy enhancing technology adoption and its impact on SMEs' performance. *Int J Eng Bus Manag* 2023 Jan 1; 15: 18479790231172874.
23. University of MichiganBagozzi R. The legacy of the technology acceptance model and a proposal for a paradigm shift. *JAIS* 2007 Apr; 8(4): 244–254.

24. Matar A and Alkhalwaleh A. Adoption of electronic cards using Wi-Fi platform services by clients of banking sector during COVID-19 pandemic. [Internet]. *Int J Eng Bus Manag* 2023; 14(3): 1–11. [cited 2023 Dec 10]. Available from. DOI: [10.1177/18479790221112797](https://doi.org/10.1177/18479790221112797)
25. Zhang T, Tao D, Qu X, et al. Automated vehicle acceptance in China: social influence and initial trust are key determinants. *Transport Res C Emerg Technol* 2020 Mar; 112: 220–233.
26. Ling LW, Downe AG, Ahmad WFW, et al. Determinants of computer usage among educators: a comparison between the UTAUT and TAM models. In: 2011 National postgraduate conference, Perak, Malaysia, 19–20 Sept. 2011.
27. Rejali S, Aghabayk K, Esmaeli S, et al. Comparison of technology acceptance model, theory of planned behavior, and unified theory of acceptance and use of technology to assess a priori acceptance of fully automated vehicles. *Transport Res Pol Pract* 2023 Feb; 168: 103565.
28. Kimiagari S and Baei F. Promoting e-banking actual usage: mix of technology acceptance model and technology-organisation-environment framework. *Enterprise Inf Syst* 2021 Apr 12; 16: 1–57.
29. Sovacool BK. Experts, theories, and electric mobility transitions: toward an integrated conceptual framework for the adoption of electric vehicles. *Energy Res Social Sci* 2017 May; 27: 78–95.
30. Kaye SA, Lewis I, Forward S, et al. A priori acceptance of highly automated cars in Australia, France, and Sweden: a theoretically-informed investigation guided by the TPB and UTAUT. *Accid Anal Prev* 2020 Mar; 137: 105441.
31. Khazaei H. The influence of personal innovativeness and price value on intention to use of electric vehicles in Malaysia. *Eur Online J Nat* 2019; 8: 483.
32. Abbasi H, Johl S, Shaari Z, et al. Consumer motivation by using unified theory of acceptance and use of technology towards electric vehicles. *Sustainability* 2021 Nov 4; 13(21): 12177.
33. Jain NK, Bhaskar K and Jain S. What drives adoption intention of electric vehicles in India? An integrated UTAUT model with environmental concerns, perceived risk and government support. *Res Transp Bus Manag* 2022 Mar; 42: 100730.
34. Khazaei H and Tareq MA. Moderating effects of personal innovativeness and driving experience on factors influencing adoption of BEVs in Malaysia: an integrated SEM–BSEM approach. *Heliyon* 2021 Sep; 7(9): e08072.
35. Dunn MG, Murphy PE and Skelly GU. Research note: the influence of perceived risk on brand preference for super-market products. *J Retailing* 1986; 62(2): 204–216.
36. Wang S, Wang J, Li J, et al. Policy implications for promoting the adoption of electric vehicles: do consumer's knowledge, perceived risk and financial incentive policy matter? *Transport Res Pol Pract* 2018 Nov; 117: 58–69.
37. Schuitema G, Anable J, Skippon S, et al. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. *Transport Res Pol Pract* 2013 Feb; 48: 39–49.
38. Huang X and Ge J. Electric vehicle development in Beijing: an analysis of consumer purchase intention. *J Clean Prod* 2019 Apr; 216: 361–372.
39. Asadi S, Nilashi M, Samad S, et al. Factors impacting consumers' intention toward adoption of electric vehicles in Malaysia. *J Clean Prod* 2021 Feb; 282: 124474.
40. Degirmenci K and Breitner MH. Consumer purchase intentions for electric vehicles: is green more important than price and range? *Transport Res Transport Environ* 2017 Mar; 51: 250–260.
41. Zhang X, Wang K, Hao Y, et al. The impact of government policy on preference for NEVs: the evidence from China. *Energy Pol* 2013 Oct; 61: 382–393.
42. Venkatesh V, Thong JYL and Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Q* 2012; 36(1): 157–178.
43. Zhou M, Long P, Kong N, et al. Characterizing the motivational mechanism behind taxi driver's adoption of electric vehicles for living: insights from China. *Transport Res Pol Pract* 2021 Feb; 144: 134–152.
44. Gunawan I, Redi AANP, Santosa AA, et al. Determinants of customer intentions to use electric vehicle in Indonesia: an integrated model analysis. *Sustainability* 2022 Feb 9; 14(4): 1972.
45. Hägerstrand T. Aspects of the spatial structure of social communication and the diffusion of information. *Pap Reg Sci Assoc Reg Sci Assoc Meet* 1966 Dec 1; 16(1): 27–42.
46. Martins C, Oliveira T and Popović A. Understanding the Internet banking adoption: a unified theory of acceptance and use of technology and perceived risk application. *Int J Inf Manag* 2014 Feb; 34(1): 1–13.
47. Zhang Y, Yu Y and Zou B. Analyzing public awareness and acceptance of alternative fuel vehicles in China: the case of EV. *Energy Pol* 2011 Nov; 39(11): 7015–7024.
48. Bhat F, Verma M and Verma A. Measuring and modelling electric vehicle adoption of Indian consumers. *Transportation in Developing Economies*. 2022 Apr 1; 8: 6.
49. Soutarh GN. Consumer perceived value: the development of a multiple item scale. *J Retail* 2001; 77: 203–220.
50. Vafaei-Zadeh A, Wong TK, Hanifah H, et al. Modelling electric vehicle purchase intention among generation Y consumers in Malaysia. *Res Transp Bus Manag* 2022; 43: 100784.
51. Masiero G, Ogasavara MH, Jussani AC, et al. The global value chain of electric vehicles: a review of the Japanese, South Korean and Brazilian cases. *Renew Sustain Energy Rev* 2017 Dec; 80: 290–296.
52. Han L, Wang S, Zhao D, et al. The intention to adopt electric vehicles: driven by functional and non-functional values. *Transport Res Pol Pract* 2017 Sep; 103: 185–197.
53. Kim MK, Oh J, Park JH, et al. Perceived value and adoption intention for electric vehicles in Korea: moderating effects of environmental traits and government supports. *Energy* 2018 Sep; 159: 799–809.

54. Thananusak T, Rakthin S, Tavewanaphan T, et al. Factors affecting the intention to buy electric vehicles: empirical evidence from Thailand. *Int J Electr Hybrid Veh (IJEHV)* 2017; 9(4): 361.
55. Globisch J, Plötz P, Dütschke E, et al. Consumer preferences for public charging infrastructure for electric vehicles. *Transport Pol* 2019 Sep; 81: 54–63.
56. Morrison G and Belle JPV. Customer intentions towards autonomous vehicles in South Africa: an extended UTAUT model. In: 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) [Internet], Noida, India: IEEE, 29–31 Jan. 2020. [cited 2023 Dec 10]. p. 525–31. Available from: <https://ieeexplore.ieee.org/document/9057821/>
57. Lashari ZA, Ko J and Jang J. Consumers' intention to purchase electric vehicles: influences of user attitude and perception. *Sustainability* 2021 Jun 15; 13(12): 6778.
58. Xu Y, Zhang W, Bao H, et al. A SEM–neural network approach to predict customers' intention to purchase battery electric vehicles in China's zhejiang province. *Sustainability* 2019 Jun 5; 11(11): 3164.
59. Bentler PM and Chou CP. Practical issues in structural modeling. *Socio Methods Res* 1987 Aug; 16(1): 78–117.
60. Golob TF. Structural equation modeling for travel behavior research. *Transp Res Part B Methodol* 2003 Jan; 37(1): 1–25.
61. Preacher KJ and Merkle EC. The problem of model selection uncertainty in structural equation modeling. *Psychol Methods* 2012; 17(1): 1–14.
62. Hair J. *Multivariate data analysis: a global perspective*. London: Pearson Education, 2010.
63. Kline RB. Response to leslie hayduk's review of principles and practice of structural equation modeling. *CSP* 2018 Aug 30; 45(3–4): 188.
64. Straub DW. Validating instruments in MIS research. *MIS Q* 1989 Jun; 13(2): 147.
65. Fornell C and Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. *J Market Res* 1981 Feb; 18(1): 39–50.
66. Hutze L and Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct Equ Modeling* 2009; 6: 1–55.
67. Jansson J, Pettersson T, Mannberg A, et al. Adoption of alternative fuel vehicles: influence from neighbors, family and co-workers. *Transport Res Transport Environ* 2017 Jul; 54: 61–73.
68. Sukathong S, Suksawang P and Naenna T. Analyzing the importance of critical success factors for the adoption of advanced manufacturing technologies. *Int J Eng Bus Manag* 2021 Jan 1; 13: 18479790211055057.
69. Azadnia AH, Onofrei G and Ghadimi P. Electric vehicles lithium-ion batteries reverse logistics implementation barriers analysis: a TISM-MICMAC approach. *Resour Conserv Recycl* 2021 Nov; 174: 105751.
70. Lee CKH and Wu KYK. Making autonomous vehicle systems human-like: lessons learned from accident experiences in traffic. *Enterprise Inf Syst* 2023 Jun 3; 17(6): 1998641.

Appendix A

Variables description reference	Description	Reference
Social Influence	SI1: People who are important to me would think that I should use EV	(Jain, Bhaskar and Jain, 2022); (Kasper and Abdelrahman, 2020)
	SI2: People who influence my behaviour would think that I should use EV	
	SI3: People whose opinion I value would prefer that I use EV	
	SI4: Driving EV would make a good impression about me on the other people	
Effort Expectancy	EE1: I would find EV easy to use	(Jain, Bhaskar and Jain, 2022); (Kasper and Abdelrahman, 2020)
	EE2: It would be easy for me to become skilful at using EV	
	EE3: My utility for EV would be clear and understandable	
	EE4: Learning how to drive EV would be easy for me	
Performance Expectancy	PE1: I would find EV useful in my daily life	(Jain, Bhaskar and Jain, 2022); (Kasper and Abdelrahman, 2020)
	PE2: Using EV would help me travel quickly	
	PE3: Using EV would increase my productivity	
	PE4: Using an electric vehicle for daily activities may be helpful in my work	
Facilitating Conditions	FC1: The public infrastructure for electric car is available	(Vafaei-Zadeh et al., 2022); (She et al., 2017)
	FC2: The electric car infrastructure at work is available	
	FC3: The electric car infrastructure at home is available	
	FC4: The electric car infrastructure on highway is available	

(continued)

(continued)

Variables description reference	Description	Reference
Price Value	PV1: EVs offers value for money PV2: Electric car is reasonably priced PV3: Electric car is economical in the long run PV4: The price paid may be in accordance with the electric vehicle that I will get	(Vafaei-Zadeh et al., 2022); (Zhang et al., 2020)
Policy Incentives	PI1: Purchase subsidies help me adopt EVs PI2: Reducing purchase-related taxes helps me adopt EVs PI3: Preferential measures such as access bus lanes helps me adopt EVs PI4: The government's charging infrastructure expansion policy helps me adopt EVs	(Kim et al., 2018); (Zhang et al., 2013)

(continued)

(continued)

Variables description reference	Description	Reference
Perceived Risk	PR1 I am afraid of suffering financial losses when using EVs PR2 I would not feel totally safe when I drive an EV on the road PR3 Considering the disadvantages of EVs (e.g., limited driving range and long time recharging), I think using EVs could involve important time losses PR4 I am worried about whether EVs will really perform as well as traditional gasoline vehicles	(Wang et al., 2018); (Junquera, Moreno and Álvarez, 2016)
Adoption Intention	AI1 I am willing to adopt an EV in the near future AI2 I plan to adopt an EV in the near future AI3 If I need to buy a new car in the near future, I would prefer an EV AI4 If my friends want to buy a new car, I would suggest to buy an EV	(Zhang et al., 2022); (Han et al., 2017)