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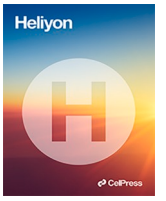

Research article

Acceptance model of new energy vehicles based on PLS-SEM model

Jing Liu [a,b,*], Nan Zhang [a], Yifan Yang [a]

[a] Economics and Management Institute, Xinjiang University, Urumqi, 830046, China
[b] Macroeconomic High-quality Development Research Center, Xinjiang University, Urumqi, 830046, China

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ABSTRACT

The current energy crisis is worsening worldwide, and in China, urban expansion and per capita vehicle ownership have created a growing energy imbalance and increased pressure to reduce carbon emissions.The popularization of new energy vehicles (NEVs) can provide a step forward to solving energy shortage problems, environmental pollution, and global warming. In 2022, the average penetration rate, which is ratio of new energy vehicle sales to vehicle sales, is just 19.1 %. This paper analysed the reasons for the differences in the penetration rates of new energy vehicles in China's 269 prefecture-level cities, using a Geo Detector approach, and the results showed that the level of economic development, the average annual temperature difference, the density of charging piles, the charging price and the number of population all had significant effects($q > 0.12$) on the penetration rate. Based on the above studies, a questionnaire was used to investigate the public's acceptance of new energy vehicles in Xinjiang Uygur Autonomous Region, and a PLS-SEM regression analysis was conducted. The results showed that men, young people and people with a certain level of basic education were 5 % more likely to accept new energy vehicles.Unlike previous studies, perceived cost had no significant correlation with the acceptance of new energy vehicles. Perceived risk had a significant negative correlation with the acceptance of new energy vehicles,the path coefficient is −0.1.The acceptance of new energy vehicles was significantly and positively correlated with vehicle quality and service, the public's understanding of new energy vehicles, and subjective norms, their average path coefficients are above 0.1. We argues that the government should maintain a certain level of promotion of new energy vehicles and accelerate the construction of charging piles, based on the aforementioned results.

1. Introduction

China's car ownership is rapidly increasing due to the acceleration of urbanisation and industrialisation, leading to a booming automotive industry. Currently, the urban transport system is the third largest carbon emission sector in the world. In 2022, China's urban transport system is projected to emit over 800 million tonnes of carbon. Additionally, the automobile industry is responsible for 25 % of greenhouse gas emissions, with potential for further increases in the future [1–3]. These emissions have significant impacts on energy supply and demand, environmental pollution, and public health. In order to protect our shared environment, countries worldwide have agreed to limit carbon emissions and are actively promoting low-carbon environmental protection. China has

* Corresponding author. Macroeconomic High-quality Development Research Center, Xinjiang University, Urumqi, 830046, China.
E-mail address: liuj@xju.edu.cn (J. Liu).

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responded to this by proposing the '2030 Carbon Peak' and '2060 Carbon Neutral' visions. To achieve 'dual-carbon' goals, it is necessary to promote a low-carbon transition in the automotive industry and urban transport systems[4,5].

New energy vehicles are a significant product of low-carbon, green, energy-saving, and environmentally friendly technology. They represent the future of urban transport system equipment and the automotive industry. Compared to fuel vehicles, NEVs can reduce carbon emissions by 30–50 % and improve fuel efficiency by 50 % [1,6–8]. Therefore, in order to achieve a low-carbon transformation of the urban transport system and the automotive industry, it is necessary to fully promote the use of new energy vehicles.

The significance of NEVs in the automotive industry and urban transport system is widely recognised by all sectors of society. In 2021, the State Council released the Action Programme for Carbon Peak by 2030, which advocates for the active expansion of new and clean energy applications in the transport sector, the promotion of low-carbon transformation of transport equipment, and the vigorous promotion of new energy vehicles [9–13]. Chinese automotive and technology companies have begun researching, developing, and producing new energy vehicles. In April 2022, BYD announced that it would cease production of fuel vehicles and transition to new energy vehicles. Similarly, technology giants Huawei and Xiaomi have also entered the new energy vehicle market. Research on new energy vehicles is also on the rise, with industry support policies, consumer subsidies and tax breaks, infrastructure development and consumer willingness to buy being current research hotspots [14–18].

However, China's new energy vehicle market share remains low due to imperfect supporting infrastructure, insufficient public awareness of NEVs, and unbalanced regional development. In 2022, the ownership of new energy vehicles in China exceeded 13 million units, but their sales accounted for only 13.4 % of total vehicle sales. There remains a discrepancy between the current state and the goal of achieving 20 % of new energy vehicle sales by 2025, as outlined in the New Energy Vehicle Industry Development Plan (2021–2035). Additionally, the adoption of new energy vehicles varies significantly across different regions of China. New energy vehicles are popular in developed regions like Beijing, Shanghai, Guangdong, and Jiangsu. However, the market for new energy vehicles is still in its early stages in less developed regions in the west, such as Xinjiang, Gansu, and Ningxia.

The western region of China is abundant in energy and mineral resources, with leading industries including coal, petrochemicals, and other high-energy-consumption, high-emission, and high-pollution sectors. The industrial structure, which is characterised by high carbon emissions, poses challenges for energy conservation, emission reduction, and pollution prevention. Promoting the widespread use of NEVs in the urban transport system in the western region and facilitating the green transformation and development of the automotive industry is of utmost urgency. Xinjiang, an important energy and chemical industry development base in China, not only has a thriving high-carbon industry, but also has a rapidly developing clean energy industry, including solar and wind energy. Using Xinjiang as an example, this study on the popularity of new energy vehicles can provide a reference for achieving green and low-carbon transformation of the automotive industry and transport system in less developed regions.

However, most current studies on the popularity of new energy vehicles begin with a micro-consumer perspective. They construct a model of new energy vehicle acceptance and use structural equations to analyze consumers' willingness to purchase new energy vehicles [5,19–23]. This approach can identify the factors that influence consumers' acceptance of new energy vehicles, but it lacks a macro perspective analysis. At the city level, the market share of new energy vehicles in China varies greatly, which is influenced by factors such as urban consumer acceptance, economic development, natural geographic environment, and industrial layout. This paper begins with a macro perspective, using the geodetector model [24] to identify the factors that contribute to differences in market share of new energy vehicles across various prefectural-level cities. Based on this analysis, we selected Xinjiang as a region for further research and distributed questionnaires to obtain micro-data for analysis. By combining macro and micro analyses, we offer various countermeasure suggestions to expedite the promotion of NEVs in urban transport systems and the green transformation of the automotive industry in less developed regions.

2. Literature review

The technology acceptance model was originally developed to investigate the likelihood and reasons for widespread computer acceptance. This model suggests that public acceptance is influenced by perceived usefulness, perceived ease of use, and attitudes [25]. These factors combine to form the public's behavioural intentions, which in turn result in varying levels of acceptance. The former refers to the extent to which a new technology can improve productivity, while the latter refers to the effort required to use the technology. Perceived usefulness and perceived ease of use are two key factors that determine the adoption of new technology. Attitude, on the other hand, refers to the positive or negative feelings that users have towards the technology or product[26–29].

The Theory of Planned Behaviour and the Technology Acceptance Model share a common theoretical foundation, namely the Theory of Rational Behaviour. However, the Theory of Planned Behaviour focuses more on external influences on an individual's behaviour. Ajzen(1988) found that individuals are not always in complete control of their behaviour. The theory of planned behaviour comprises five elements: attitudes, subjective norms, perceived behavioural control, behavioural intentions, and behaviour [30]. Behavioural intentions are influenced by attitudes, subjective norms, and perceived behavioural control, and guide individuals to take actual actions. Attitudes, which are largely consistent with those in the technology acceptance model, refer to an individual's positive or negative feelings about a behaviour. Subjective norms refer to social pressures on individuals, meaning that their behaviour is influenced by the behaviour of others. Perceived behavioural control refers to the influence of past experiences and future expectations on an individual's behavioural decisions [31–35].

The acceptance of new energy vehicles has been the subject of extensive research. It refers to the public's inclination towards purchasing and using these vehicles, as reflected in their evaluation and expected purchasing behaviour [36]. Previous studies have demonstrated that the public's willingness to buy is negatively affected by perceived risk and cost. The quality and service of the vehicle, as well as government support policies, can significantly increase the public's willingness to buy [37]. Additionally, the

public's values affect their purchasing behaviour, with those who prioritize environmental protection and social fairness being more inclined to purchase and use new energy vehicles [36,38–41].

Furthermore, most macro-level studies on urban areas concentrate on the general advancement of the new energy vehicle industry [42–46]. They examine the effects of factors such as technology maturity, technical standards, capital investment, and industrial policies on the industry's development. However, there is a dearth of analysis on the public's inclination to purchase. The Geo Detector method has been extensively used in natural and social sciences since its proposal in 2010. This method is free from the assumption of linearity, can detect spatial heterogeneity, and reveal the driving factors [24]. It has certain advantages in identifying macro-influential factors at the city level.

Compared to developed regions, the use of new technologies in less developed regions can have more positive effects. The distinctive technological and innovative advantages of new energy vehicles can enable relatively less developed regions to achieve innovation-driven development and make progress in low-carbon transport and low-carbon city construction[4,10,47,48]. Therefore, it is important to study the acceptance of new energy vehicles in less developed regions [49]. However, most of the current research on the acceptance of new energy vehicles focuses on economically developed cities and regions, with less research on less developed regions.

This paper aims to investigate public purchase intention of new energy vehicles from both macro and micro perspectives by combining the Geo Detector method and the study of new energy vehicle acceptance.

3. Macro analysis

3.1. Research hypotheses

The penetration rate is an important factor to the acceptance of new energy vehicles. In 2022, the average penetration rate of new energy vehicles in China is only 19.3 %. What factors affect the popularity of new energy vehicles?

First, new energy vehicles are complementary and alternative to traditional fuel vehicles, their popularity is inextricably linked to economic status and demographic factors. Unlike traditional fuel cars, the power battery of new energy vehicles has strict requirements for the natural environment [50–53]. In addition, new energy vehicles have higher requirements on infrastructure, the layout of charging piles and charging price will affect the promotion of new energy vehicles [54–56]. Based on the above analysis, this paper proposes a hypothesis: the level of economic development, population status, natural environment and infrastructure level are all related to the popularity of new energy vehicles, and the conceptual research hypothesis is shown in Fig. 1.

3.2. Descriptive statistics

We selected 269 prefecture-level cities nationwide and collected their basic economic data, new energy vehicles' sales, penetration rate, and number of charging piles in 2022 for analysis. Some cities in the provinces of Tibet, Yunnan, Sichuan, and Heilongjiang, where data are missing, are removed from the scope of the study.

This paper selected the new energy vehicles' penetration rate as a macro indicator of new energy vehicles acceptance and GDP per capita as an indicator of economic development level. Meanwhile, we adopted the average annual temperature difference as a measure of natural environment and charging pile density, charging fee as an indicator of infrastructure.

Among them, the penetration rate is calculated by extrapolating vehicle sales from traffic insurance data published by the China Automotive Industry Association (CAIA).The 2023 China Urban Statistical Yearbook provides data on GDP and population; the temperature difference is calculated using the monthly average temperature from the ERA5-LAND data set. In April 2023, we manually collated online data from the eCharge app to obtain information on the number of charging piles, charging prices, and charging service fees. Table 1 shows a list of variables and as shown in Fig. 2 & Fig. 3, the penetration rate and charging pile density have obvious geographical divisions.

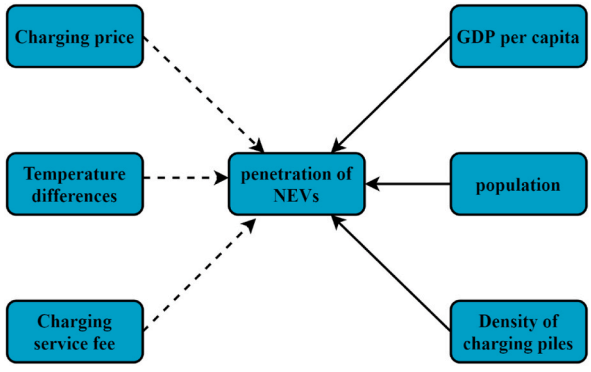

Fig. 1. Conceptual research hypothesis.

3.3. Geo Detector

Spatial differentiation is one of the fundamental characteristics of geographic phenomena. Geo Detectors are tools for detecting and exploiting spatial variability [24]. The Geo Detectors consists of four components: variance and factor detection, interaction detection, risk area detection, and ecological detection. Divergence and factor detection is used to detect the spatial variability of Y and the extent to which X explains the spatial variability of the attribute Y. formula (1)&(2) are

$$q = 1 - \frac{\sum_{h=1}^{L} Nh\sigma^2 h}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{1}$$

$$SSW = \sum_{h=1}^{L} Nh\sigma^2 h \ , \ SST = N\sigma^2 \tag{2}$$

Interaction detection identifies the interaction between different factors Xs, i.e., it assesses whether factor $X1$ enhances or weakens the explanatory power of the dependent variable Y when acting together with $X2$. It is assessed by first calculating the q-values of $X1$ and $X2$ on Y separately, then calculating the q-values when they interact, and comparing $q(X1)$、$q(X2)$、 $q(X1 \cap X2)$.

3.4. Results

3.4.1. Spatial dispersion and factor detection

The results of the geographic detector analysis in Table 2 showed that GDP per capita, population, charging pile density of new energy vehicles, charging service fee, charging price and annual average temperature differences all had significant effects on the penetration rate of NEVs. Among them, charging pile density and temperature differences have the greatest influence on the penetration rate, with q-values of 0.54 and 0.43, respectively.

3.4.2. Interaction detection

As shown in Fig. 4, the results of interaction detection showed that there was a non-linear enhancement relationship between the factors: charging pile density and service fee, population and GDP per capita, temperature differences, charging price, service fee, temperature difference and charging price, charging price and service fee; while there is a two-factor enhancement relationship between charging pile density and population, GDP per capita, temperature difference, charging price, and temperature difference and service fee. This indicates that different factors, when acting together, can have a greater impact on the acceptance of new energy vehicles.

4. Case analysis

4.1. Research hypotheses

Based upon the Theory of Planned Behavior and the Technology Model Acceptance, this paper selects the 'attitude' construct from the Theory of Planned Behavior as the primary factor and simultaneously considers three other factors: external social factors, new energy vehicle product characteristics, and the public's internal factors, to build a new acceptance model for new energy vehicles [57]. The external social factors in the model include subjective norms and supportive policies. New energy vehicle product factors include perceived risk, perceived cost, new energy vehicle quality and service, and new energy vehicle characteristics. Internal factors of the public include the public's understanding of new energy vehicles, environmental protection awareness, and life value orientation [58–60].

Attitude refers to the basic preference formed by conceptualizing an individual's evaluation of a certain behavior. If the public has a more positive attitude towards new energy vehicles, they will be more inclined to purchase and use them [38,39,61]. Based on the above analysis, the following assumption is proposed:

H1. The public's attitude towards new energy vehicles has a significant positive impact on the acceptance of new energy vehicles.

Table 1
Variables.

	variables	methods
Explained variables	penetration rate	NEVs sales/Vehicles sales volume
Explanatory variables	GDP per capita	GDP/population
	population	Resident population
	Temperature differences	Yearly maximum temperature - Yearly minimum temperature
	Density of charging piles	Number of Charging Piles/City Area
	Charging service fee	Average charging service fee
	Charging price	Average charging price

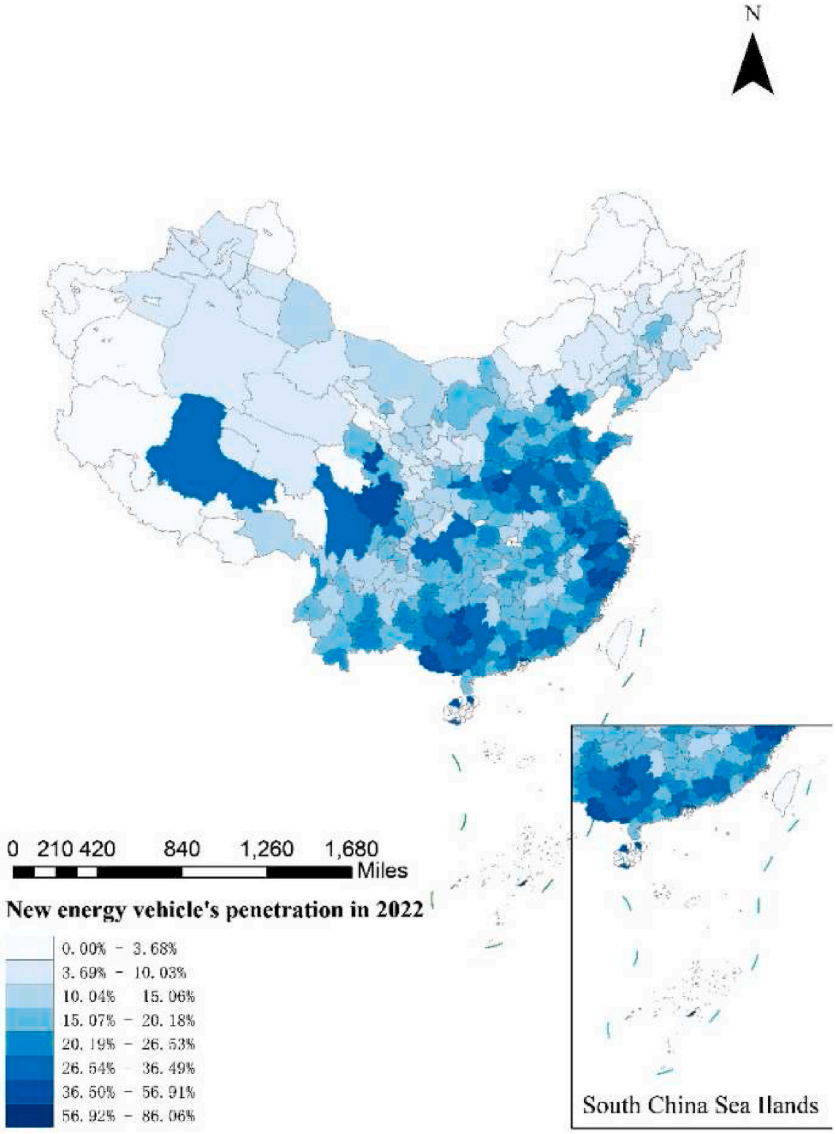

Fig. 2. The penetration rate of NEVs.

Because the expected outcome of the customers' purchasing behavior cannot be confirmed, the decision to purchase implies the uncertainty of the results, which is known as perceived risk. Consumers may make impulsive decisions because they do not have sufficient expert knowledge. However, once consumers are aware of the possible risks of new energy vehicles, their acceptance will decrease accordingly. In addition, perceived risk also has an important impact on attitude. The following assumptions can thus be made:

H2a. The public's perceived risk of new energy vehicles has a significant negative impact on the level of acceptance.

H2b. The perceived risk of the public on new energy vehicles has a significant negative impact on the attitude and thus has a significant negative impact on the acceptance.

Cost is an important factor for the public to choose new technologies or products, especially when it comes to nonessentials. It is advantageous for products when their cost aligns with public expectations. A study by Shen [62] showed that Chinese consumers generally dislike buying expensive technology products. In addition, higher costs will also lead to higher perceived risks for the public; therefore, they will be reluctant to choose new energy vehicles [63]. The above analysis leads to the following assumptions:

H3a. The perceived cost of the public on new energy vehicles has a significant negative impact on the acceptance.

H3b. The perceived cost of the public on new energy vehicles has a significant negative impact on the basic attitude and thus has a

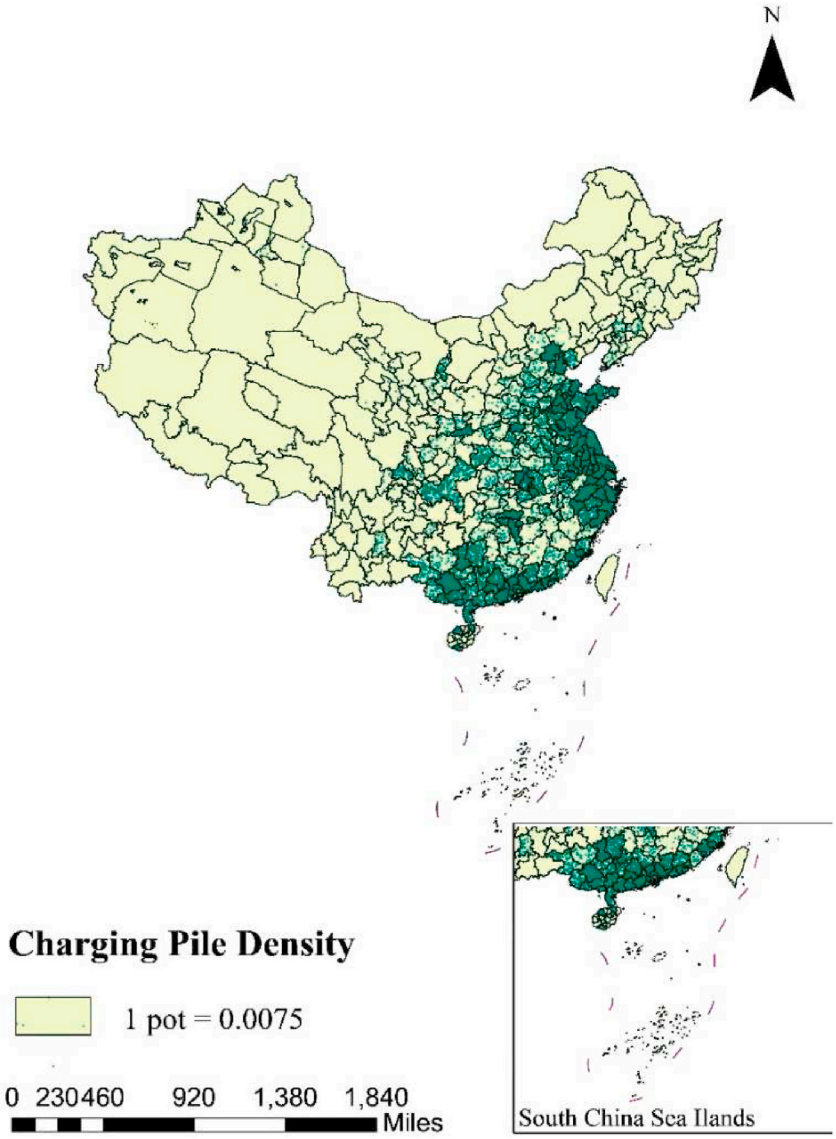

Fig. 3. The charging pile density.

Table 2
Spatial dispersion and factor detection results.[a,b]

factors	q statistic
population	0.18[c]
GDP per capita	0.12[c]
temperature differences	0.43[c]
charging pile density	0.54[c]
charging price	0.15[c]
service fee	0.14[c]

Notes.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

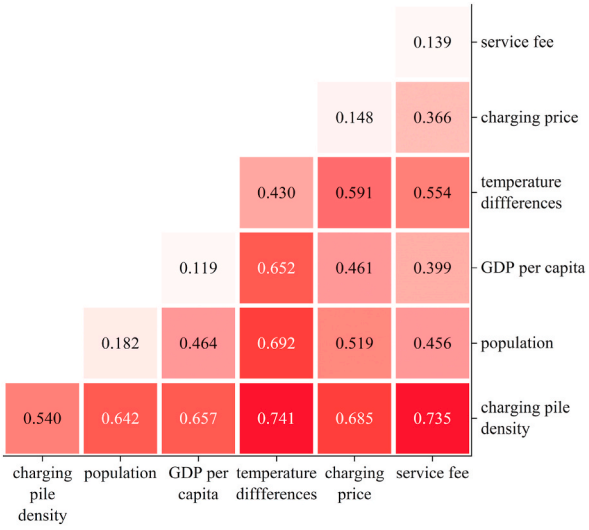

Fig. 4. Interaction detection results.

significant negative impact on the acceptance.

H3c. The public's perceived cost of new energy vehicles has a significant positive impact on perceived risk.

Product quality and service are important measures of perceived ease of use. Products that can meet the user's needs to a greater extent are more likely to be accepted by the market. The following assumptions are thus made:

H4a. The quality and service of new energy vehicles have a significant positive impact on acceptance.

H4b. The quality and service of new energy vehicles have a significant positive impact on attitude.

The new energy vehicles in the Chinese market currently are unique in design appearance, and characteristic customization is provided. For example, Wuling Hongguang MINI introduced customized vehicle body appearance while Weilai Automobile provides customized services for automotive parts and built-in functions. Personalized new energy vehicles can demonstrate the owner's taste or personality. It can be assumed that:

H5a. The personalized customization service and the distinctive design appearance of new energy vehicles have a significant positive impact on the degree of acceptance.

H5b. The personalized customization service and distinctive design appearance of new energy vehicles have a significant positive impact on attitude.

The Chinese government has long supported the development of the new energy vehicle industry through preferential policies to promote the popularity of new energy vehicles. The following assumption is thus made:

H6. The government's support policies significantly impact the acceptance of new energy vehicles positively.

Subjective norms refer to the social pressure individuals feel when they engage in specific behaviors. According to the Theory of Planned Behavior, no individual behavior is based on independent rational decision-making. China's long-standing 'acquaintance society' model has made individuals more vulnerable to external influences [39,63]. The following assumption is thus made:

H7. Subjective norms significantly impact the acceptance of new energy vehicles positively.

People tend to buy products they are more familiar with. If the public lacks knowledge about NEVs, it may hinder the development of new energy-related technologies. People who know more about the charging time, battery life, and product design of new energy vehicles will be more inclined to purchase new energy vehicles [47]. The following assumptions can thus be made:

H8a. The public's knowledge of new energy vehicles has a significant positive impact on the acceptance of new energy vehicles.

H8b. The public's knowledge of new energy vehicles has a significant negative impact on perceived risk.

With the proposal of the 'double carbon' goal and the promotion of low-carbon city construction, the public has a stronger awareness of environmental protection and low-carbon emission reduction [4,48,64]. They try to contribute to solving the problems of energy shortage and environmental pollution by purchasing low-carbon green products and opting for a low-carbon lifestyle [39,65]. Compared to traditional fuel vehicles, using small new energy vehicles in urban distribution systems can reduce carbon emissions by more than 48 % [66]. The following assumptions are thus made:

H9a. The public's awareness of environmental protection has a significant positive impact on the acceptance of new energy vehicles.

H9b. Public awareness of environmental protection has a significant positive impact on attitude.

The individual's life value orientation may also impact their behavior. Individuals who pay more attention to environmental protection may prefer to use NEVs, while individuals who pay more attention to power and wealth may choose products that can better highlight their social status. Niu [38] divided individual value orientation into three groups, namely, power and wealth-oriented, social equity-oriented, and environmental protection oriented [67–69]. Through analysis, it was found that different value orientations have different impacts on the public's acceptance of new energy vehicles. Therefore, this paper proposes the following assumptions:

H10a. The public's value orientation of altruism and environmental protection has a significant positive impact on the acceptance of new energy vehicles.

H10b. The public's value orientation of altruism and environmental protection has a significant positive impact on environmental awareness.

In summary, the Conceptual path analysis model in SEM is shown in Fig. 5.

4.2. Data

4.2.1. Data collection

In case study, online and offline questionnaires were distributed among the people of Xinjiang to investigate their awareness of new energy vehicles and their willingness to use them. Ethical approval was obtained for this study from Xinjiang University.The initial questionnaire was distributed among 15 people randomly interviewed offline, and modifications to the questionnaire were made based on the information gathered. The final questionnaire was released in April 2022, and the whole data collection process lasted four months. The online questionnaire data were collected through an online survey on Wenjuanxing (www.wjx.com), an online platform equivalent to Amazon Mechanical Turk, and the offline questionnaire data was collected through interviews. A total of 1068 questionnaires were obtained, of which 47 were invalid. After eliminating the invalid questionnaires, 1021 valid questionnaires remained, showing a questionnaire efficiency rate of 95.6 %. The questionnaire consisted of two parts: basic information and the public's acceptance of new energy vehicles. The first part included gender, age, education level, family structure, income, and car use habits, among others. The second part included but was not limited to the public's attitude towards new energy vehicles, perceived risks, perceived costs, supporting policies, knowledge, and purchase intentions, which were measured using a five-point Likert scale with the exception of the measurement of the public's value of orientation (Question 30). To answer this question, the participants were required to rank the importance of the three given different value orientations in decreasing order. This data was re-scored prior to data modeling and analysis. The option ranking first was assigned three points, and the assigned scores decreased with decreasing order of importance. As shown in Fig. 6, the questionnaire data were collected from 14 prefecture-level cities in Xinjiang, covering a wide range of regions. The majority of the participants were from Urumqi, accounting for 54.36 % of the participants. Thus, the regional distribution of questionnaire participants was relatively reasonable.

4.2.2. Descriptive statistics

As shown in Table 3, 52.2 % of the participants were male, 47.8 % were female, 65.43 % were younger than 35 years old, and 74.93 % had a bachelor's degree or above. More than 50 % of the total sample population had an annual family income below 150,000 RMB.

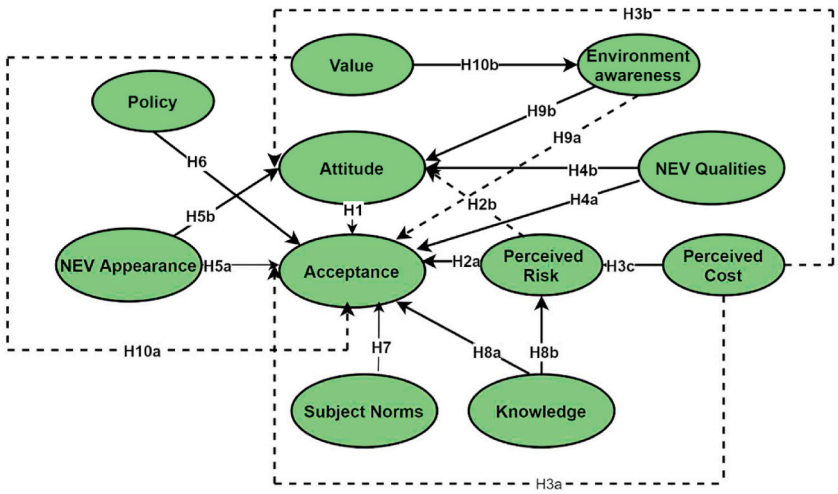

Fig. 5. Conceptual path analysis model in SEM.

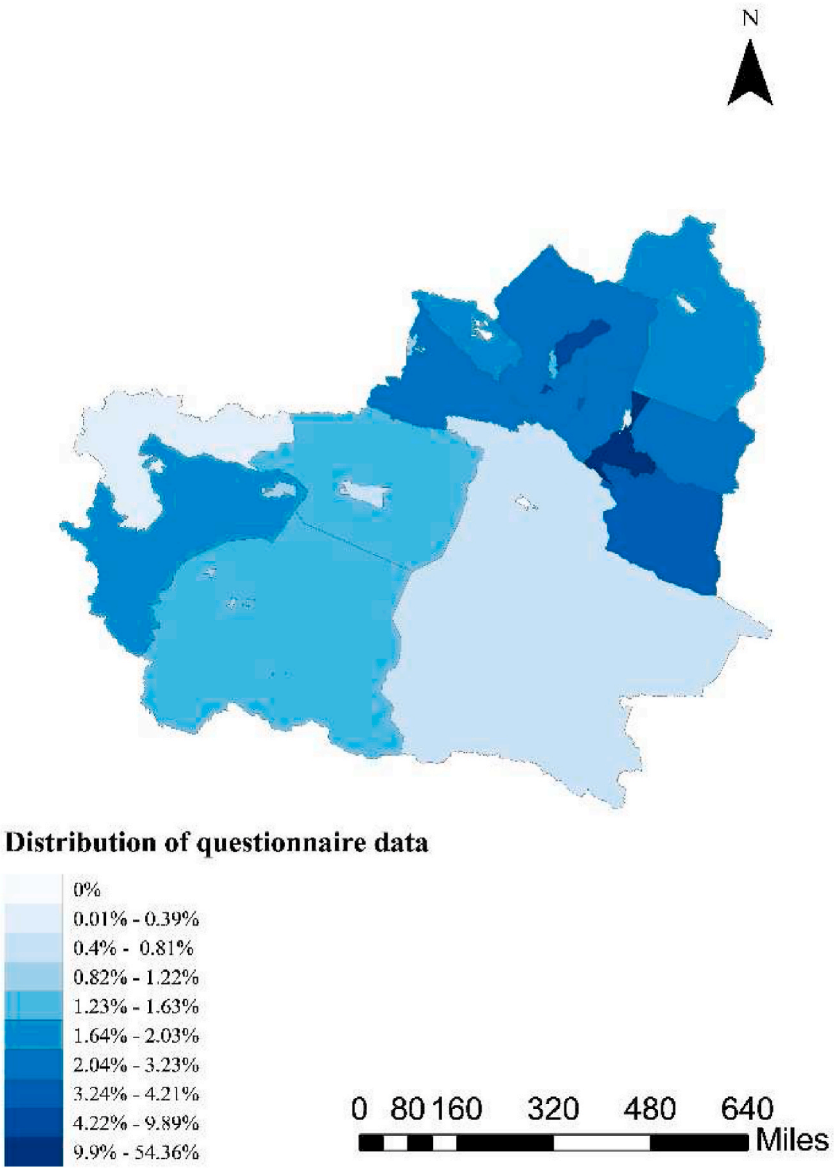

Fig. 6. Distribution of questionnaire data.

Table 3
Characteristics of participants.

Variable	Item	Percentage (%)	Mean value of inclination	Variable	Item	Percentage (%)	Mean value of inclination
Gender	Male	49.59	3.9	Annual household income	≤8	19.51	3.51
	Female	50.41	3.86	(10000RMB)	8–12	24.59	3.83
Marital	Married	53.25	4.04		12–15	18.09	4.01
status	Unmarried	46.75	3.72		15–20	20.53	4.02
Age	≤25	32.11	3.69		20–30	12.2	4.14
	25–35	40.85	4.09		≥30	5.08	3.85
	35–50	21.95	3.9	Acceptable price	≤5	4.26	3.61
	≥50	5.08	3.42	(10000RMB)	5–8	16.19	4.01
Education	Middle school and below	6.5	4		8–15	46.02	4.13
	High school	12.6	4.22		15–35	28.69	4.18
	Undergraduate	45.53	3.95		35–50	3.98	4.68
	Graduate	35.37	3.66		≥50	0.85	5

People in Xinjiang were strongly willing to purchase and use new energy vehicles. Age, education level, income, family structure, marital status, owning a driver's license and a car, years of driving, and the acceptable price of new energy vehicles, all had a certain impact on the acceptance of new energy vehicles. Among people with an annual income of less than 300,000 RMB, the higher the income was, the higher the acceptance of new energy vehicles was. Married people had a significantly higher acceptance of new energy vehicles than unmarried people. The participants aged 25–35 had the highest acceptance of new energy vehicles. The acceptance varied among people with different educational backgrounds. People with a high school education had the highest acceptance, while people with master's degrees or above had the lowest acceptance of new energy vehicles. Moreover, the questionnaire data showed that people who were interested in new energy vehicles were mainly buying them to improve the circumstances of their family, in terms of vehicle, which is also consistent with the phenomenon that car owners have a higher acceptance of new energy vehicles.

4.3. Method

4.3.1. PLS-SEM modeling

Structural equation modeling (SEM) combines factor analysis with regression analysis. SEM can clearly analyze the interactions between independent variables and dependent variables, as well as the interactions between dependent variables, and the detectability of the relationship between variables is converted from exploratory to confirmatory analysis [70,71]. In this study, Stata 16.2 was used to implement partial least squares structural equation modeling (PLS-SEM). formula(3) is as follows:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

Where, ξ is a vector of exogenous latent variables, η is a matrix of endogenous latent variables, B is a coefficient matrix indicating the effect among the constituent factors of η, Γ is another coefficient matrix representing the effect of ξ on η, and ζ indicates the residual matrix, representing the unexplained parts [72].

4.3.2. Mediation effect

The mediation effect model can be used to investigate the process and mechanism of how the independent variable X influences the dependent variable Y. Compared with similar studies with simple analysis of the influence of X on Y, the mediation analysis is not only improved in the method but obtains more in-depth results. In the process of exploring the influence of X on Y, if X has an influence on Y by affecting M, then M is called a mediator variable. formulae(4),formula(5)and formula(6) are as follows:

$$Y = cX + e1 \tag{4}$$

$$M = aX + e2 \tag{5}$$

$$Y = c'X + bM + e3 \tag{6}$$

Where, the coefficient c in equation (4) is the gross effect of the predictor variable X on the predicted variable Y, the coefficient a in equation (5) is the effect of the predictor variable X on the predicted variable Y, the coefficient b in equation (6) is the effect of the mediator variable M on the dependent variable Y while controlling for the effect of the independent variable X, the coefficient c' in equation (6) is the direct effect of the predictor variable X on the predicted variable Y while controlling for the mediating effect of the mediator variable M, and $e1 \sim e3$ are the regression residuals.

4.4. Results

4.4.1. Reliability & validity test and model fit analysis

To verify the rationale of the questionnaire design, reliability and validity tests were conducted after collecting the first 120 questionnaires. The questionnaire adopted the Likert scale, commonly using Cronbach's α as coefficient (reliability coefficient) to test the reliability and the average variance extracted (AVE) coefficient to measure the convergent validity of the questionnaire. Existing research usually adopts $\alpha > 0.7$, AVE >0.5 as the reliability and validity test standards, but Tabachnick and Fidell [73] also suggested that they can be eased to 0.6 and 0.4, respectively. In our study, because of the many items in the questionnaire, we used $\alpha > 0.6$ and AVE>0.4 as the standard. Statistical analysis was done using SPSS and the results showed that the questionnaire had a Cronbach α

Table 4
Reliability and validity tests and model fit.

Item	CR	AVE	ITEM	CR	AVE
Attitude	0.844	0.576	SN	0.787	0.483
PR	0.819	0.532	Appearance	0.633	0.413
PC	0.812	0.591	EA	0.723	0.467
QS	0.758	0.514	Policy	0.612	0.402
KN	0.730	0.474	Total	0.832	0.442
ITEM	KMO	Bartlett	r^2	AGOF	RGOF
Total	0.907	0.000	0.655	0.631	0.974

value of 0.832 and each latent variable of α was valued between 0.612 and 0.844. This indicates that the questionnaire showed high reliability. At the same time, the validity of the questionnaire was tested and evaluated by KMO and Bartlett's tests. As shown in Table 4, the KMO of all potential variables was 0.907, and the Bartlett test value was 0.000 < 0.01. Moreover, the overall AVE coefficient was 0.442, and the AVE coefficients of all latent variables were between 0.402 and 0.576. The questionnaire thus had good structural validity and was suitable for hypothesis testing.

The model fit analysis for the PLS-SEM model is relatively complex and has yet to reach a final conclusion. Excluding R2 value in existing standards, the most common way to assess model fit is to use redundancy and goodness of fit (GoF) indices for evaluation. The Strata 16.2 software for PLS-SEM was used for structural equation modeling and analysis. As shown in Table 4, r2 was 0.65495, and AGOF was 0.63060, both higher than 0.6. The RGOF was 0.97413, significantly greater than 0.9, and all fit indices of the model met the requirements of the AGOF greater than 0.6 and the RGOF greater than 0.9. Therefore, this model is suitable for analyzing the factors that affect the public's acceptance of new energy vehicles.

4.4.2. Measurement model verification

The PLS-SEM measurement model mainly uses p value and standardized loadings to evaluate the model effect. The results are shown in Table 5. The p values of all potential variables in the measurement model are less than 0.01, and the measurement model is significant. Moreover, the absolute value of standardized loadings of different indices falls within the range of 0.537–0.909, meeting the model fit requirement of standardized loadings greater than 0.5 [74]. ALL fit indices of the model met the requirements of the p value less than 0.1 and the standardized loadings greater than 0.5. Considering the calculated data, this model can measure the latent variables needed for research through the explicit variable index.

4.4.3. Verification of structural model

The results of the verified structural model are shown in Table 6, which supports the assumptions H1, H2a, H3c, H4a, H4b, H5a, H5b, H6, H7, H8b, H9b, and H10b. This suggests that the public's attitude, the quality and service of new energy vehicles and subjective norms are significantly positively related to public acceptance of NEVs in underdeveloped areas. Meanwhile, the characteristic design and design service of new energy vehicles, the government's support policies and the public's knowledge about new energy vehicles are significantly positively correlated to public acceptance of NEVs.

However, the perceived risk and the public's acceptance of new energy vehicles in underdeveloped regions are significantly negatively correlated, and the public's knowledge of new energy vehicles is significantly negatively correlated to perceived risk. There were no significant correlation between perceived cost and public acceptance of NEVs.

Strong positive correlations exist among perceived cost to perceived risk, subjective norms to purchase intent, environmental awareness to attitudes, and value judgement to environmental awareness. The correlation between quality and service to attitudes, knowledges to purchase intentions is relatively weak.

4.4.4. Mediation effect test

Based on the test results of the Structural Equation Model, the test of the mediation effect was conducted for some paths that had been shown to be significant. As shown in Table 7, in the 95 % confidence interval, the two paths of environmental awareness → attitude → acceptance, and value orientation → environmental awareness → acceptance, were significant. This shows that the stronger the public's awareness of environmental protection, the more positive their attitude toward new energy vehicles, thus the easier it was to accept new energy vehicles. At the same time, the preference of personal value orientation towards environmental awareness will make the public more aware of environmental protection, thus they will have a more positive attitude towards new energy vehicles.

Table 5
Measurement model – Standardized load.

Item	Standardized load	Item	Standardized load
Attitude 1	0.737	Knowledge 3	0.876
Attitude 2	0.733	Subject Norms 1	0.818
Attitude 3	0.818	Subject Norms 2	0.790
Attitude 4	0.753	Subject Norms 3	0.766
Perceived risk 1	0.724	Subject Norms 4	0.765
Perceived risk 2	0.890	Appearance 1	0.795
Perceived risk3	0.835	Appearance 2	0.933
Perceived risk 4	0.537	Environmental awareness 1	0.783
Perceived cost 1	0.789	Environmental awareness 2	0.730
Perceived cost 2	0.876	Environmental awareness 3	0.860
Perceived cost 3	0.909	Policy 1	0.778
Quality and service 1	0.756	Policy 2	0.908
Quality and service 2	0.791	Value 1	−0.476
Quality and service 3	0.862	Value 2	−0.442
Knowledge 1	0.832	Value 3	0.987
Knowledge 2	0.798		

Table 6
Test results of Structural Equation Model.

Structural Equation test results			
Assumptions	Path	Path coefficient	Result
H1	ATTITUDE→PI	0.155[c]	Support
H2a	PR→PI	−0.1[c]	Support
H2b	PR→ATTITUDE	0.099	No support
H3a	PC→PI	0.003	No support
H3b	PC→ATTITUDE	0.031	No support
H3c	PC→PR	0.665[c]	Support
H4a	QS→PI	0.127[c]	Support
H4b	QS→ATTITUDE	0.074[a]	Support
H5a	APPEARANCE→PI	0.199[c]	Support
H5b	APPEARANCE→ATTITUDE	0.197[c]	Support
H6	POLICY→PI	0.149[c]	Support
H7	SN→PI	0.285[c]	Support
H8a	KN→PI	0.088[b]	Support
H8b	KN→PR	−0.068[b]	Support
H9a	EA→PI	0.067	No support
H9b	EA→ATTITUDE	0.478[c]	Support
H10a	VALUE→PI	−0.016	No support
H10b	VALUE→EA	0.252[c]	Support

Notes.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

Table 7
Mediation effect test results.[a,b]

Mediation effect test			
Path	Path coefficient	Z-statistic	Result
EA→ATTITUDE→PI	0.296[c]	8.426	Support
VALUE→EA→ATTITUDE	0.183[c]	6.188	Support

Notes.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

5. Discussion

The macro-analysis results indicate that temperature difference, GDP per capita, charging pile density, charging price, and charging service fee significantly affect the penetration rate of new energy vehicles. The prevalence of two-factor augmented and non-linear augmented interactions is also evident. Among these factors, temperature difference, population, and charging pile density have the greatest impact. It is suggested that regions with large temperature differences, low population density, poor supporting facilities, and more backward economic development, such as the Northwest and Northeast regions, have lower public acceptance of new energy vehicles.

After analysing the data from the micro-questionnaire, it was found that the acceptance of new energy vehicles varies among individuals due to significant differences in age, education level, income, marital status, and car use habits. The study found that 25–35 year olds were more accepting of new energy vehicles compared to other age groups, which is in line with the results of Potoglou et al. (2007) who discovered that young people in Hamilton preferred non-traditional fuel vehicles [75].

Although individuals with higher levels of education are generally more receptive to new technologies and products, the results of this study indicate that among all respondents, those with a high school education demonstrated the highest level of acceptance. Conversely, among those with a bachelor's degree or higher, the level of acceptance decreased as their education level increased. The reasons for this are twofold. However, they also tend to view new energy vehicles as less mature and reliable than traditional fuel vehicles. Firstly, participants with higher levels of education tend to have greater knowledge and interest in new energy vehicles, particularly in terms of cost-effectiveness, range, safety and technological maturity. Secondly, participants with higher levels of education also tend to have higher expected income levels, which often leads them to choose mid-to high-end vehicles. However, China's current new energy vehicles are mostly low-end and mid-range, which does not align with their needs.

Families with four members who are married are more likely to be open to purchasing new energy vehicles due to their higher demand for car use. Additionally, large families may be able to meet their growing demand for cars by purchasing a new energy vehicle, even if they already own a fuel vehicle. The study's data supports the finding that over 40 % of participants who are interested

in buying a new energy vehicle want to enhance their family's car environment.

In line with previous research, the public's perception of risk associated with new energy vehicles has a significant negative impact on their acceptance. Consumers tend to be more receptive to low-risk technologies and products due to the high level of uncertainty and potential losses associated with high-risk options [47]. In the first quarter of 2022, fires caused by new energy vehicles in China increased by 32 %, which is higher than the average annual growth rate of automotive fires of 8.8 %. This is due to the fact that EV batteries are more likely to burn after a collision, unlike the closed tank systems of fuel vehicles. This could heighten public awareness of the risks associated with new energy vehicles, potentially decreasing their appeal to consumers [76–78].

Our results indicate that perceived cost does not significantly affect the acceptance of new energy vehicles, which differs from previous studies. Egbue and Long [79] found that the public's acceptance of new energy vehicles would not increase unless the price of fuel was significantly increased. Since 2022, petrol prices have risen repeatedly due to the Russian-Ukrainian war, resulting in a surge in the cost of using conventional fuel vehicles. After years of development, the battery life of new energy vehicles has been improved to meet public demand. Furthermore, the gradual improvement of supporting facilities, such as charging stations, and the excellent performance of new energy vehicles have convinced the public that there is no significant cost disadvantage of new energy vehicles compared to traditional fuel vehicles [80].

In line with previous research, the quality and services of new energy vehicles have a positive impact on public attitudes and acceptance. The public is more willing to purchase and use new energy vehicles when the range meets their daily needs, the after-sales service is of high quality, and the urban support facilities are adequate. Furthermore, new energy vehicles offer distinct advantages in terms of their exterior design and customization services. For instance, the Wuling Hongguang MINI and LI AUTO vehicles boast captivating exterior and interior customization options, which have significantly enhanced public acceptance of new energy vehicles.

6. Conclusions

The acceptance of new energy vehicles by the public is influenced by various selling factors. This paper conducts a micro-analysis of consumer acceptance of new energy vehicles by distributing a questionnaire survey, based on the analysis of macro-influencing factors at the city level.

This paper presents a geographic vector analysis of cross-sectional data from 269 prefecture-level cities in 2022. The results indicate that cities with smaller temperature differences, higher charging pile density, lower charging prices, higher per capita GDP, and higher population densities have a higher penetration of new energy vehicles. The language used is clear, objective, and value-neutral, with a formal register and precise word choice. The text adheres to conventional structure and formatting features, with consistent citation and footnote style. The structure is logical, with causal connections between statements and a clear progression of information. The text is free from grammatical errors, spelling mistakes, and punctuation errors. No changes in content have been made. The battery life of new energy vehicles can be significantly impacted by large temperature differences. A more comprehensive charging infrastructure could enhance public perception of new energy vehicles.

This paper selected Xinjiang, where the penetration rate is the lowest, as a typical region for the questionnaire survey based on the above analyses. The empirical study of the PLS-SEM model, based on the questionnaire data, shows that men and young people have a higher acceptance level. This differs from Wang Rong's findings in 2022, which indicated that females have a higher acceptance level. The higher acceptance of males in the Xinjiang region may be due to the fact that there were more males in the group that participated in the questionnaire. Young people are more likely to accept new energy vehicles due to their attitude of embracing change and being active in life.

Perceived risk has a negative impact on acceptance, consistent with existing research. The public's willingness to purchase new energy vehicles is significantly reduced by their perception of potential risks, such as poor battery life, inconvenient charging, and insufficient range [81,82]. Furthermore, the acceptance of new energy vehicles is positively influenced by their quality and service, as well as their unique exterior design and customised offerings. Improved quality and special customised services increase public satisfaction when using these vehicles. Niu's study found that people who prioritize social justice and environmental protection are more likely to choose new energy vehicles. The public's values and awareness of environmental protection also play a role in this decision. It is important to avoid subjective evaluations and maintain a clear, objective language with precise word choice. The text should adhere to conventional structure and formatting features, while avoiding filler words and colloquial expressions. The language should remain formal and free from grammatical errors, and the content should not deviate from the original text.

Previous studies have found a negative correlation between perceived cost and the acceptance of new energy vehicles. However, this paper's findings indicate no such correlation. This could be attributed to the recent increase in fuel prices, which has highlighted the cost advantages of new energy vehicles. Some studies have suggested that government policies are becoming less effective in promoting public purchasing behaviour. However, this research does not support that claim. Currently, the public remains sensitive to government policies, and subsidies and tax incentives continue to be important factors in their decision to choose new energy vehicles.

Based on the above results, it is recommended that the government adjusts measures according to local conditions and continues to maintain certain subsidy incentives to further release the public's purchasing power [83,84]. Additionally, the lack of charging infrastructure for new energy vehicles may significantly impede the public's adoption of these vehicles. To tackle the issues of insufficient charging infrastructure and high charging fees, regions with low electric vehicle adoption rates should proactively plan the deployment of charging stations and provide subsidies to charging station operators to lower the cost and risk of using electric vehicles [85].

The impact of subjective norms and environmental awareness on the acceptance of new energy vehicles is significant [86]. To enhance consumers' understanding of new energy vehicles, enterprises should strengthen publicity. The government should also

increase its efforts in environmental protection publicity to raise public environmental awareness and promote the green and low-carbon labelling of new energy vehicles, which will, in turn, encourage the purchase and use of new energy vehicles.

For new energy vehicle enterprises, the quality, service, and special design of their vehicles are key business assets. Upgrading vehicle design and manufacturing, as well as improving product and service quality, can significantly increase public interest in purchasing these vehicles [87].

This paper analyses the factors that influence public purchase and use of new energy vehicles from both macro and micro perspectives. However, it does not consider the technological progress of new energy vehicles, industrial layout, and other relevant factors. The industrial layout of new energy vehicles and energy storage technology will be further investigated.Meanwhile, the acceptance model of new energy vehicles proposed in this paper failed to include important influencing factors such as perceived behavioral control, consumption concept, and regional culture. In the future, we will consider the impact of culture, perceived behavioral control, and consumption concept on the acceptance of new energy vehicles.

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Data availability statement

The data used and analysed in this study are available on request from the corresponding author at smileliuj@126.com.

CRediT authorship contribution statement

Jing Liu: Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Nan Zhang:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Yifan Yang:** Visualization, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e30350.

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