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Heterogeneous Factors Influencing Electric Vehicle Acceptance: Application of Structural Equation Modeling

Weishang Guo [1,2,3], Jian Huang [2], Wei Chen [2,*], Yihua Mao [3], Desire Wade Atchike [1] and Munir Ahmad [4,5]

[1] School of Civil Engineering and Architecture, Taizhou University, Taizhou 318000, China; wsguo@tzc.edu.cn (W.G.); wade1738@tzc.edu.cn (D.W.A.)
[2] Era Co., Ltd., Taizhou 318020, China; huangjian@era.com.cn
[3] College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China; maoyihua@zju.edu.cn
[4] College of International Economics & Trade, Ningbo University of Finance and Economics, Ningbo 315175, China; munirahmad@nbufe.edu.cn
[5] "Belt and Road" Bulk Commodity Research Center, Ningbo University of Finance and Economics, Ningbo 315175, China
* Correspondence: wchen@era.com.cn

Abstract: Since electric vehicle (ELV) deployment can contribute to overall renewable energy sources, exploration of the heterogeneous influence factors (HIFs) affecting the willingness to accept ELVs can assist in the realization of sustainable development goals, particularly *universal access to affordable energy for all*. In this research, we explored the HIFs that influence the willingness of individuals to accept ELVs (WAELV) within an integrated decision-making (IDM) framework. We established the IDM conceptual framework through the incorporation of HIFs, notably including the environmental and health benefits of ELVs, knowledge about innovation, and the benefits regarding the built environment and creating a comprehensive structure. We analyzed data gathered through questionnaires from urban and peri-urban areas of the Shandong province (China) by employing the partial least square structural equation modeling technique, which is an appropriate tool for analyzing data measured on a Likert scale. The key findings were as follows. Firstly, the capital cost of ELVs was found to be a significant barrier to the WAELV of individuals. Secondly, among other factors, the societal aspect of ELVs and the environmental awareness aspect were drivers of the WAELV of individuals across all the data samples. However, benefits for the built environment, knowledge about innovation, and the environmental and health benefits of ELVs only positively drove the WAELV of individuals in the urban setting and for the overall sample. Thirdly, these three HIFs were identified as neutral factors in the peri-urban areas. Thus, a clear disparity was detected between the urban and peri-urban areas in terms of factors influencing the WAELV of individuals. Finally, the social aspect of ELVs was revealed as the strongest driver, while benefits for the built environment turned out to be the weakest factor. Based on these findings, some crucial policies are here extracted.

Keywords: heterogeneous influence factors; electric vehicle acceptance; integrated decision-making conceptual framework; environmental and health benefits; knowledge about innovation; benefits for the built environment; structural equation models

1. Introduction

In the wake of the green energy revolution, electric vehicle (ELV) acceptance may increase its contribution as China faces the same environmental unsustainability dilemma as other global countries. It is commonplace to believe that there are numerous factors causing the global underprivileged growth of ELVs, including the capital cost of ELVs, the absence of appropriate legislation, and a lack of awareness of environmental issues [1]. In this regard, all relevant stakeholders of ELVs expect incentivized and subsidized market

and regulatory frameworks to overcome the socioeconomic barriers to the acceptance of ELVs [2]. In addition to all these expectations, the perceived value of ELVs by customers has remained essential to the acceptance of ELVs. In this context, three factors involving the capital cost of ELVs (CCELV), environmental awareness (ENAW), and societal aspects of ELVs (SAELV) were studied in some form among the mainstream studies [3–5]. Song and Potoglou [6] found that ELVs' market extension is likely to be assured by competitive ads, promotional programs, and the responsiveness of individuals to its benefits. In other words, the scale of individual approval for ELVs will likely depend on several other factors. When deciding on the assessment and procurement of new products like ELVs, knowledge about environmental issues and innovations are considered the primary factors involved.

In previous decades, numerous researchers have examined how individuals make decisions regarding the willingness of individuals to accept ELVs (WAELV) when choices require a trade-off between the different costs and benefits associated with ELVs [7]. In this regard, mainstream studies emphasize the significant aspects influencing the desirability of ELVs. For example, a Hong Kong-based study included 180 respondents and used structural equation modeling (SEQM) to discover that customer satisfaction and green trust interfered with the relationship between WAELV and procurement purposes [8]. Furthermore, Breschi et al. [2] used a human-centric framework based on survey data to analyze ELV acceptance through a quantitative investigation of the adaptability of human habits in choosing ELVs. In prior studies, the advancement and use of ELVs were taken into account in the following ways: (i) influence factors of WAELV in the context of Big Five personality traits [9]; and (ii) functional and mass market influence factors of battery ELVs were studied to observe the feasibility of accepting ELVs [5]. Finally, some of the studies employed the theory of planned behavior to evaluate customers' WAELV in the context of various samples [10,11]. Nevertheless, the prior studies conducted in the context of ELVs did not take into account the benefits for the built environment (BBEN), knowledge about innovation (INKN), or the environmental and health aspects of ELVs (EHELV). Thus, the investigation of the heterogeneous influence factors (HIFs) affecting the WAELV of individuals has been limited, and no studies have been known to take into account urban and peri-urban heterogeneity while studying the HIFs affecting the WAELV of individuals.

Given the backdrop of significant research gaps, we aimed to empirically analyze the drivers and barriers of the WAELV of individuals in an integrated decision-making (IDM) conceptual framework while considering the novel HIFs involving BBEN, INKN, and EHELV. The inclusion of these HIFs extend allowed for novel contributions to existing knowledge. Considering the BBEN, individuals' perceptions of ELV adoption as a way to reduce environmental emissions and lead to indoor air quality improvement was expected play a decisive role in the WAELV of individuals. Furthermore, turning to INKN, as ELVs involve innovative technologies, knowledge about innovation can contribute to the WAELV of individuals. Most notably, the inclusion of the EHELV was critical for the IDM since individuals attach the utmost importance to environmental and health concerns, particularly in developed regions and countries. In this regard, BBEN, INKN, and EHELV had the potential to present heterogeneous influence mechanisms for the urban and peri-urban data framed by this study. As a step further, we analyzed the urban and peri-urban data of China's Shandong province to signify the disparity between urban and peri-urban areas. We employed a partial least square (PLS)-SEQM to analyze the articulated hypotheses through a questionnaire based on one hundred and fifty-two participants from five prefectural cities and their associated counties in the Shandong province. The empirical findings of the work then allowed us to propose essential policies. The statistical inferences of this study stand alone amongst the existing studies. For illustration, as recorded in the foregoing details, BBEN, INKN, and EHELV have never been adopted as the critical factors affecting WAELV in any of its configurations. We have found these factors to be significant drivers of WAELV in urban areas, while these factors played a neutral role in peri-urban areas. Additionally, we introduced all these HIFs to the IDM conceptual framework for the first time to provide a comprehensive modeling framework for upcoming studies.

Relating to the significance and scope of the findings, although they are extracted from data from certain geographical localities of China, the derived inferences reveal the influencing aspects of a global phenomenon regarding the WAELV of individuals, and thus, the findings are not assumed to be case-specific. Moreover, the innovative aspects involving BBEN, INKN, and EHELV are likely to apply to all developing and developed worlds. Along these lines, China is taken as a representative case to examine the WAELV of individuals. The PLS-SEQM is considered the most suitable choice to analyze the constructs of latent variables (LTVs), so it is considered a cutting-edge method.

The remainder of the paper is structured as follows: Section 2 describes the building of a conceptual framework band, formulating the hypotheses into an integrated decision-making (IDM) conceptual framework. Section 3 focuses on data analysis strategies. Section 4 deals with the results and a discussion of the structural model. Finally, Section 5 reports the key conclusions and policies.

2. Conceptual Framework and the Formulation of Hypotheses

This section is devoted to the building of an integrated decision-making (IDM) conceptual framework based on existing and novel heterogeneous influence factors (HIFs). This framework is shown in Figure 1. It also formulates the hypotheses to be tested in this study based on empirical and theoretical discussions.
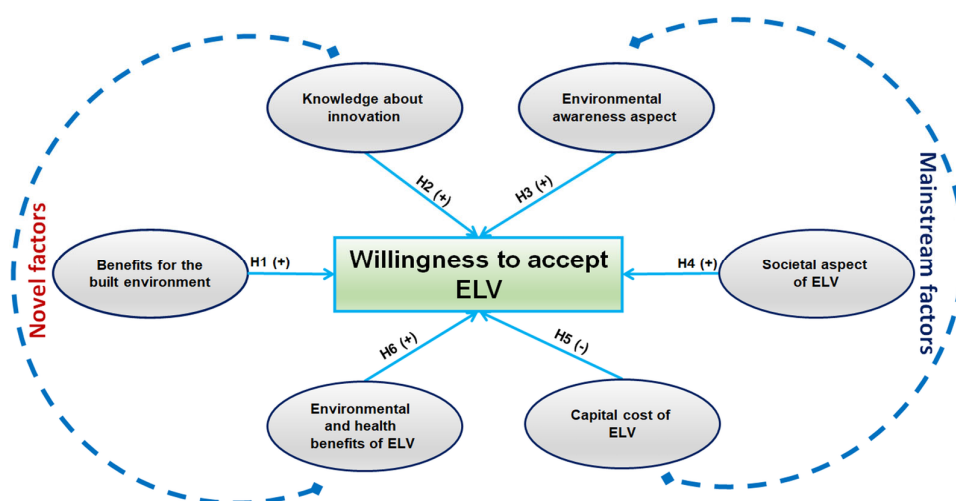

Figure 1. An integrated decision-making (IDM) conceptual framework showing the HIFs influencing the WAELV of individuals. *Source:* authors' drawing.

2.1. Benefits for the Built Environment (BBEN)

The BBEN associated with the use of ELVs may provide fuel to the WAELV of individuals. In this context, He et al. [12] examined 22 people's experiences with embracing and utilizing ELVs via quasi-questionnaires. Their findings demonstrated that socioeconomic, cultural, behavioral, and ecological variables all have a major impact on ELV acceptability. The economic boost was the most significant factor in this respect. Using the person contentment index measure, another study discovered that the contentment of the public was greatest with regard to green power when compared to gasoline, bioenergy, and electric power. Consumer contentment was due to the perceived advantages, market demand, commodity or technological competence, and post-sales assistance [13]. Based on this evaluation, the derived hypothesis was as follows:

Hypothesis 1 (H1): *The BBEN is expected to impart a positive influence on the WAELV of individuals.*

2.2. Knowledge about Innovation (INKN)

Innovation value is the perceived usefulness derived from a substitute's capability to stimulate interest, offer newness, and fulfill an aspiration to acquire knowledge [14]. From an Australian consumer perspective, Loengbudnark [15] used the technology acceptance theory to examine the socioeconomic factors of ELV adoption. They found age to be a significant contributor, while education played an insignificant role in ELV acceptance. An individual's knowledge is pertinent to their likelihood of buying a green energy product [13]. One's knowledge of new products plays a significant role in the purchasing of ELVs. Similarly, Triguero et al. [16] discovered the significance of adding INKN as an essential aspect of the IDM conceptual framework. For example, when individuals purchase green energy products such as ELVs, they will be morally satisfied as the purchase positively contributes to environmental concerns [17]. The innovative psychological benefits include self-expressive advantages, a warm glaze, and a familiarity with nature [18]. Other existing works confirmed INKN as a critical aspect influencing the WAELV of individuals. Based on this analysis of the existing studies, the following hypothesis was derived:

Hypothesis 2 (H2): *INKN is expected to impart a positive influence on the WAELV of individuals.*

2.3. Environmental Awareness Aspect (ENAW)

Environmental awareness is "the perceived environmental usefulness derived from a substitute as an outcome from a particular circumstance faced by an individual who is making a choice to purchase a product" [19]. In this respect, Sumrin et al. [20] highlighted that the ENAW is dependent on a variety of sociological, environmental, and significant factors that aid in the improvement of SAELV and BBEN. Wu et al. [21] utilized a fixed effects model to examine the links between PM2.5 emissions and ELV acceptance at China's provincial level. The authors revealed that ELV acceptance significantly reduced those emissions. By applying SEQM, Ahmad et al. [22] delved into the factors affecting biogas technology approval by rural residents of Pakistan. Their findings displayed that the relative advantages of environmental awareness, among others, were imperative for the approval of said technology. Mpoi et al. [23] applied a discrete choice modeling framework to study the impact of environmental awareness and other demographic features on ELV acceptance in Greece. The authors found the role of environmental awareness to be significant in determining the adoption behavior of Greek consumers. Moreover, various contextual factors provide operative and situational contexts that may promote or hinder environmentally favorable efforts [24]. The particular situations in which ENAW is significant include government-approved incentives and subsidies to promote ELV usage [25], simple accessibility to ELVs, and environmental issues [26]. In light of the above literature, it is confirmed that special situations, as discussed above, are the main factors that affect the purchasing behavior of individuals towards ELVs. In view of this, the following hypothesis is shaped:

Hypothesis 3 (H3): *ENAW is expected to impart a positive influence on the WAELV of individuals.*

2.4. Societal Aspect of ELVs (SAELV)

Societal value has been opined as the "perceived usefulness of a substitute derived from its impression in link with socioeconomic, demographic, and cultural groups" [27]. Societal value essentially indicates individuals' perceptions regarding the thoughts and responses of the general public if he or she were to buy an ELV. Moreover, it has been shown that an individual's opinion towards acquiring a product is impacted by the sociological group in which they are a member [28]. People use green energy items to save money and to build and maintain social connections [25]. It has also been said that status quo employees like to purchase such things in order to maintain a certain level of prestige; this is also the goal behind purchasing something [29]. Sahoo et al. [30] applied SEQM to Indian data to inspect the social and positive factors affecting ELV acceptance and

revealed social factors to be supportive of such an acceptable behavior. In their research, Jabeen et al. [31] investigated the perception elements of renewable technology acceptance in Pakistan by applying SEQM to primary data. They revealed that the societal aspects of those technologies were influential in the urban areas, while they proved neutral in the countryside economy. Personal factors such as the views of an individual's family, colleagues, and neighbors also have a largely favorable impact on a person's desire to purchase an ELV [32]. Based on this, the following hypothesis was extracted:

Hypothesis 4 (H4): *The SAELV is expected to impart a positive influence on the WAELV of individuals.*

2.5. Capital Cost of ELVs (CCELV)

The expense associated with a good is substantially related to the utility obtained from its usage [33]. Qin and Ozturk [34] highlighted in their analysis that Bangladesh must transition to sources of clean power in order to fulfill rising energy needs while also reducing costly oil imports and fossil fuels. According to Qian and Yin [35], one of the primary challenges to embracing ELVs is the high capital cost of such innovations. Setiawan et al. [36] made use of the causal loop diagrammatic framework to examine the socioeconomic factors of ELV acceptance in Indonesia. They discovered that high taxation on ELVs impeded their acceptance. A study by Paradies et al. [37] employed survey-based data from prospective consumers of ELVs in the Netherlands to inspect the influence of pricing and driving range on future ELV acceptance. They found that the pricing factor was a barrier to ELV acceptance among the sampled data. Additionally, Wu et al. [38] conducted a study of 210 people in China to investigate the influence of contributing variables on participants' WAELV. Their research revealed that the high cost of ELVs compared to other typical gasoline vehicles was the key factor in ELV adoption. In their research, Rahmani and Loureiro [23] investigated the contributing elements of renewable acceptability by applying SEQM to data from 200 families throughout Spain. The important results demonstrated that the lack of an energy facility in remote areas, as well as high costs, were among the major elements influencing people's WAELV. Following this discussion, the formulated hypothesis was as follows:

Hypothesis 5 (H5): *The CCELV is expected to impart a negative influence on the WAELV of individuals.*

2.6. Environmental and Health Benefits of ELVs (EHELV)

Environmental and health benefits refer to the usefulness obtained from any product because of a decrease in its long- and short-term perceived cost in terms of environmental and health damages [1]. The functional value is assessed after a rational analysis of different advantages involving environmental and health benefits and the expenditures incurred in buying a product. Every rational individual wants to attain the maximum advantage of a product at the lowest possible expense. From a related perspective, Jabeen et al. [39] examined the factors affecting biogas technology acceptance by applying propensity score matching methods to Pakistani data. They revealed that health benefits remained a paramount concern for households in choosing biogas technology. In addition, Pata [40] observed that pricing was the primary factor for deciding to switch to renewable electricity. Irfan and Ahmad [9] also studied the different traits of ELVs which might contribute to their value to individuals and explained that ecological benefit is one of the critical traits for individuals, who are willing to pay an even higher price to purchase ELVs. Therefore, from the above discussion, it is theorized that the environmental and health benefits of ELVs are among the vital influencing aspects of the WAELV of individuals.

Hypothesis 6 (H6): *The EHELV are expected to impart a positive influence on the WAELV of individuals.*

3. Data Analyses

3.1. Data and Econometric Technique

To constitute the scale items of the constructs under analysis, we considered the following Likert scales: one denotes "strong disagreement", two indicates "disagreement", three shows "neutrality", four stands for "agreement", and five is indicative of "strong agreement".

For this pilot study, the questionnaire-based data were compiled from urban and peri-urban areas of the Shandong province of China. In this regard, we randomly selected Shandong's five prefecture-level cities (Jinan, Dezhou, Yantai, Weifang, and Linyi) and their peri-urban localities, called counties. In terms of urban data, we collected data from at least one district from each city's urban locality. From the peri-urban areas, we selected at least one county from each prefectural city on a random basis, in which we collected questionnaire responses from participants. We circulated an aggregate of 170 questionnaires (i.e., 85 in each urban and peri-urban area). Consequently, 152 questionnaires were found to have been filled correctly and completely, resulting in a response rate of 89.41%. This response rate is considered an excellent one since any rate above 20% was taken as a good response rate by previous studies [41,42].

SEQM was used to evaluate the performance of the model. The PLS-SEQM approach is a variance-based SEQM technique used to infer connecting processes between latent components (LTCs). By the same token, it enables the estimation of the detailed causal link between the LTCs. In the aftermath of structural features, despite the fact that PLS-SEQM is not infallible and is relatively succinct, it is effective in resolving two eccentricities: first, its dispensation from data distribution hypotheses; second, it eliminates the possibility of a small sample bias issue [43]. Moreover, since this work is based on an actual investigation of the HIFs influencing WAELV, the PLS-SEQM is more appropriate in this context than other approaches, including regarding the role of covariance [44]. The PLS-SEQM was carried out using the IBM SPSS Amos 23.0 statistical package.

Following the proposition made by Bollen [45], the SEQM was specified as follows:

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{1}$$

where the vectors η and ξ are the demonstrations of endogenously and exogenously determined LTCs, respectively. The vector ζ captures the residuals of the LTCs, while β and Γ are the depictions of matrices of parameters for endogenously and exogenously determined LTCs, respectively.

$$x = \lambda_x\xi + \delta \tag{2}$$

$$y = \lambda_y\eta + \varepsilon \tag{3}$$

where the measurable variables' parts can be viewed in Equations (2) and (3). In this regard, the vector x displays the exogenously determined variables, while vector y is based on endogenously determined variables. In addition, λ_x and λ_y capture the matrices of parameters associated with x and y vectors. Finally, δ and ε are the depiction of measurement errors of exogenously and endogenously determined variables.

3.2. Measurement Model Estimation

The key characteristics of data, such as mean and standard deviation, were examined. To examine the discriminant validity (DVL) element, the square roots of the extracted average variance (SREAV) values were calculated. Similarly, in the context of similar investigations in past studies [46,47], a DVL element was calculated to assess how extensively the elements of the LTCs were theoretically non-correlated. The necessary requirements of DVL evolved to be met for all LTCs as a consequence of the notion that the values of SREAV outweighed the number of correlations with the other LTCs. In the context of the

research of Sarstedt et al. [48], we confirmed the level of credibility of our measurement model (see Table 1).

Table 1. Discriminant validity results.

Data	Factors	BBEN	INKN	ENAW	SAELV	CCELV	EHELV	WAELV
Aggregate data	*BBEN*	[0.89]						
	INKN	0.276	[0.84]					
	ENAW	0.372	0.267	[0.80]				
	SAELV	0.294	0.370	0.274	[0.86]			
	CCELV	0.181	0.583	0.485	0.468	[0.82]		
	EHELV	0.174	0.482	−0.101	0.489	0.391	[0.81]	
	WAELV	0.353	0.310	0.573	−0.382	0.479	0.602	[0.79]
Peri-urban areas	*BBEN*	[0.88]						
	INKN	0.482	[0.83]					
	ENAW	0.493	0.317	[0.78]				
	SAELV	0.278	0.329	0.512	[0.80]			
	CCELV	0.375	0.491	−0.531	0.401	[0.77]		
	EHELV	0.593	0.504	0.452	0.478	0.427	[0.84]	
	WAELV	0.469	0.483	0.378	−0.366	0.119	0.290	[0.76]
Urban areas	*BBEN*	[0.76]						
	INKN	0.510	[0.80]					
	ENAW	0.358	0.465	[0.82]				
	SAELV	0.389	0.469	0.428	[0.78]			
	CCELV	0.401	0.572	−0.510	0.486	[0.81]		
	EHELV	0.448	0.317	0.148	0.583	0.289	[0.80]	
	WAELV	0.479	0.412	0.362	−0.192	0.376	0.470	[0.84]

Note: ELV: electric vehicle, **BBEN:** benefits for the built environment, **INKN:** knowledge about innovation, **ENAW:** environmental awareness aspect, **SAELV:** societal aspect of ELV, **CCELV:** capital cost of ELV, **EHELV:** environmental and health benefits of ELV, **WAELV:** willingness to accept ELV. [ ] contains the SREAV score.

On the other hand, the convergent validity (CVL) feature was computed and assessed. This aspect demonstrates the degree to which constructions' theoretical foundations apply to analogous circumstances. To confirm the CVL, both factor loadings and the average variance extracted (AVEX) were calculated. If the AVEX scores were more than 0.50, it was presumed that the LTCs effectively regulated at a minimum 50 percent of the parameter discrepancies, as shown in Table 2. Only after the setup of confirmatory factor analysis (CNFA) was the suitability of the measurement model evaluated. In general, CNFA-based loadings with scores of at minimum 0.7 were kept [49]. The composite reliability (CRL) examination also served to evaluate the inside consistency of structures. Table 2 displays these observations. The CRL results ranging from 0.7 to 0.95 attest to the effectiveness of this examination.

Table 2. Results of the SEQM measurement model.

Constructs	Aggregate Data			Peri-Urban Areas			Urban Areas		
	Outer Loadings	CRL	AVEX	Outer Loadings	CRL	AVEX	Outer Loadings	CRL	AVEX
Willingness to accept ELVs (WAELV)		0.872	0.802		0.835	0.797		0.815	0.801
WAELV1	0.797			0.778			0.751		
WAELV2	0.725			0.720			0.794		
WAELV3	0.813			0.737			0.839		
Environmental and health benefits of ELVs (EHELV)		0.814	0.780		0.800	0.764		0.798	0.763

Table 2. *Cont.*

Constructs	Aggregate Data			Peri-Urban Areas			Urban Areas		
	Outer Loadings	CRL	AVEX	Outer Loadings	CRL	AVEX	Outer Loadings	CRL	AVEX
EHELV1	0.706			0.701			0.811		
EHELV2	0.778			0.813			0.735		
EHELV3	0.723			0.765			0.704		
EHELV4	0.462			0.734			0.781		
EHELV5	0.767			0.769			0.768		
EHELV6	0.802			0.705			0.794		
Capital cost of ELVs (CCELV)		0.796	0.765		0.791	0.782		0.769	0.751
CCELV1	0.710			0.818			0.747		
CCELV2	0.762			0.758			0.751		
CCELV3	0.801			0.831			0.812		
CCELV4	0.755			0.772			0.790		
Societal aspect of ELVs (SAELV)		0.798	0.772		0.795	0.776		0.789	0.757
SAELV1	0.799			0.628			0.764		
SAELV2	0.792			0.694			0.759		
SAELV3	0.689			0.752			0.833		
SAELV4	0.761			0.791			0.817		
Environmental awareness aspect (ENAW)		0.845	0.810		0.732	0.714		0.806	0.788
ENAWA1	0.697			0.739			0.801		
ENWA2	0.753			0.687			0.710		
ENAW3	0.784			0.715			0.756		
ENAW4	0.803			0.776			0.835		
Knowledge about innovation (INKN)		0.861	0.815		0.840	0.817		0.748	0.724
INKN1	0.749			0.725			0.758		
INKN2	0.712			0.802			0.792		
INKN3	0.721			0.830			0.703		
Benefits for the built environment (BBEN)		0.792	0.754		0.765	0.731		0.775	0.742
BBEN1	0.783			0.713			0.735		
BBEN2	0.815			0.774			0.796		
BBEN3	0.764			0.716			0.824		
BBEN4	0.832			0.757			0.808		

Note: CRL denotes composite reliability, while AVEX denotes average variance extracted.

4. Structural Model Results and Discussion

As a first step in determining the reliability and coherence of the measurement model, the structural model was used to derive the postulated path coefficients that represented the factors of influence. As a result, certain critical aspects for evaluating the structural model were handled. The path coefficients of HIFs (PHIFs) were evaluated and rated in terms of their relevance and relative intensities to the first deciding element. According to Hair et al. [50], the size of the PHIFs must be more than 0.1 in order to explain a relevant influence of the construct inside the model. Additionally, the threshold of significance in resampling methodologies such as bootstrap should be at least 0.05 [51]. Because the PLS-SEQM did not take into account the data's normalization criteria, a nonparametric bootstrap approach was used to determine whether the PHIFs and external factor loading were significant. According to Hair et al. [52], gathering a minimum of 5000 replicated sampling sets based on the given sampling data is essential. The 'with replacement' technique was used to generate these samples and computed the coefficients of each produced sample. As a result, this produced a bootstrap-based distribution. According to previous studies [52,53], if less than or equal to 0.05, a PHIF is considered non-zero and significant at the 5% level. As per this deciding criterion, the hypothesized relationships were accepted for all the variables in

the urban data and aggregate data. However, the hypotheses for BBEN, INKN, and EHELV were not accepted in the peri-urban areas. These findings are recorded in Table 3.

Table 3. Structural modeling results.

Data	Hypotheses	Paths	PHIFs	Decision	VIFS	f^2	R^2	Q^2
Aggregate data	H1	BBEN → WAELV	0.361 ***	Acceptance	2.485	0.091	0.801	0.358
	H2	INKN → WAELV	0.518 ***	Acceptance	3.201	0.131		
	H3	ENAW → WAELV	0.376 ***	Acceptance	2.673	0.095		
	H4	SAELV→ WAELV	0.598 ***	Acceptance	1.062	0.151		
	H5	CCELV → WAELV	−0.701 ***	Acceptance	2.670	0.177		
	H6	EHELV → WAELV	0.465 ***	Acceptance	1.982	0.118		
Peri-urban data	H1	BBEN → WAELV	0.135	Rejection	3.678	0.034	0.739	0.360
	H2	INKN → WAELV	0.118	Rejection	3.002	0.030		
	H3	ENAW → WAELV	0.299 ***	Acceptance	1.364	0.076		
	H4	SAELV→ WAELV	0.529 ***	Acceptance	1.584	0.134		
	H5	CCELV → WAELV	−0.631 ***	Acceptance	2.580	0.160		
	H6	EHELV → WAELV	0.194	Rejection	1.256	0.049		
Urban data	H1	BBEN → WAELV	0.379 ***	Acceptance	2.574	0.096	0.762	0.351
	H2	INKN → WAELV	0.537 ***	Acceptance	2.983	0.136		
	H3	ENAW → WAELV	0.402 ***	Acceptance	1.562	0.102		
	H4	SAELV→ WAELV	0.623 ***	Acceptance	6.485	0.158		
	H5	CCELV → WAELV	−0.721 ***	Acceptance	4.274	0.183		
	H6	EHELV → WAELV	0.486 ***	Acceptance	2.492	0.123		

Note: PHIFs: path coefficient of heterogeneous influence factors, **VIFS:** score of variance inflation factor. *** denotes a probability value less than a 0.05 level of significance.

Next, R^2 was also evaluated as a second deciding feature. This assessed the degree to which the conceptions explain differences in unobservable variables (UNVs). The computed R^2 (0.810) verified the structural model's predictive importance in dealing with the reality that it outperformed the baseline value of 0.35, as supported by the previous literature [49]. After that, f^2 was evaluated as a third important feature, revealing the effect size to assess the participation of the exogenous construct in the observed variations of the endogenous UNVs (see Figure 2). A Q^2 gauge suggested by Stone [54] and Geisser [55] was assessed as a fourth crucial factor. Its non-zero score (0.492) may have spoiled the precision of the modeling setup and the analytical relevance of the generated elements of the LTCs. According to Ketchen [56], if the scores of the variance inflation factor are less than 10, this indicates the absence of multicollinearity (see Table 3).
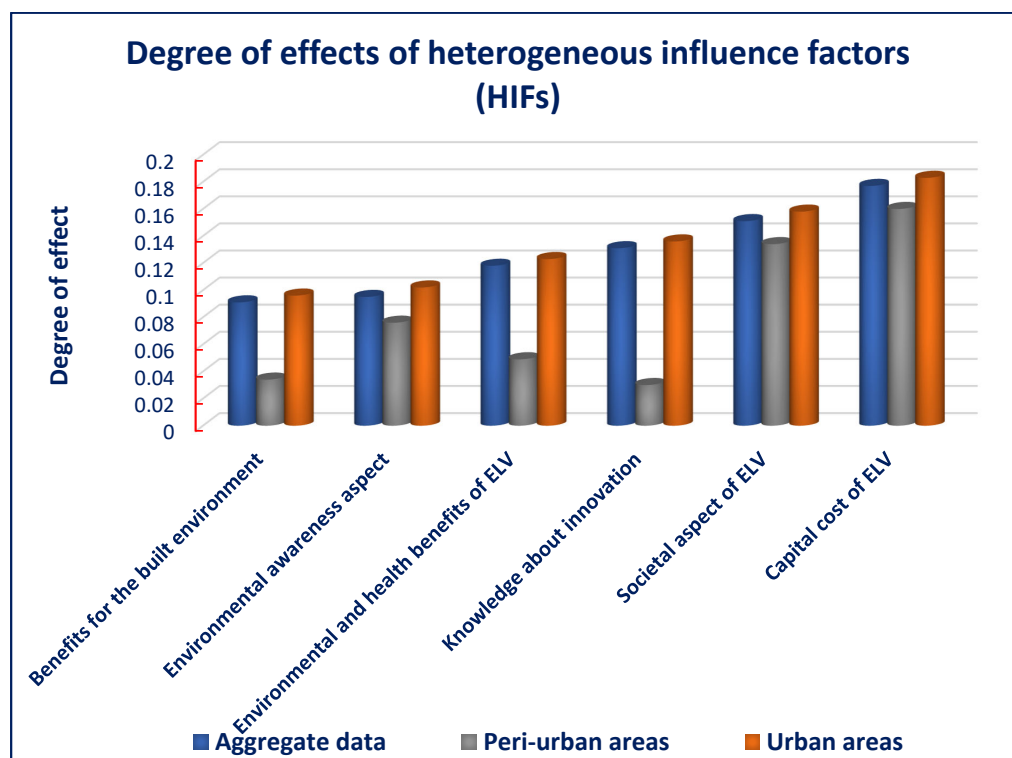
Figure 2. Degree of effects of HIFs on the WAELV of individuals across various data samples. *Source:* authors' computation based on PLS-SEQM results.

All the PHIFs were found to be significant in the case of data from urban areas and the aggregate data. However, with regard to the peri-urban data, BBEN, INKN, and EHELV appeared to be insignificant. In contrast to our findings regarding EHELV, Jabeen et al. [39] empirically observed that the health benefits aspect of biogas technology was a prevalent driving force of the acceptance of that technology in the rural areas of Pakistan. However, BBEN, INKN, and EHELV were proven to be neutral factors in the current study. Regarding INKN, a prior study by Loengbudnark et al. [15] showed conventional education to be a neutral factor of ELV acceptance by Australian consumers. In the case of the urban sample, the effect sizes of ENAW, SAELV, and CCELV exceeded those in the peri-urban areas. All of the PHIFs produced positive impacts on the WAELV, except for CCELV, which was the only factor found to have a negative effect. These findings are comparable to those of Setiawan et al. [36], who discovered the negative influence of ELV taxation on ELV adoption amongst Indonesian consumers. In parallel, Paradies et al. [37] also determined the high price of ELVs as a barrier to their adoption; however, they further observed that this barrier would be less intensive by 2030. Given these results, the HIFs were grouped into three categories: (i) drivers, (ii) barriers, and (iii) neutral factors. In this regard, ENAW and SAELV were found to be drivers of the WAELV of individuals across all the data samples. Relating to ENAW, previous work on biogas technology acceptance empirically proved that the relative advantage of innovative technology had central importance in Pakistan [22]. Moreover, Wu et al. [21] verified a significant connection between ELV acceptance and PM2.5 emissions in China, verifying the existence of an empirical link between the two variables. Turning to SAELV, our results confirmed those of Sahoo et al. [30] found in India. Our results also presented partial similarity to those of Jabeen et al. [31], as they found societal aspects to be the prominent driver of renewable energy technology acceptance on a city scale in Pakistan; however, those aspects were found to be neutral on rural scales. A different study revealed the overall positive influence of societal aspects of green energy technologies on the adoption of such technologies [57]. Moreover, CCELV was found to be a significant barrier to the WAELV of individuals across all the data samples. This finding demonstrates

some similarity with that of Ahmed et al. [58], as they concluded that the high capital cost of new technologies such as biodigester had adverse effects on social approval of such technologies in the Khyber Pakhtunkhwa Province of Pakistan. However, BBEN, INKN, and EHELV were peculiar in that these HIFs appeared to be drivers of WAELV across the aggregate data and in urban areas but became neutral factors in the peri-urban areas. These factors are categorized in Figure 3.
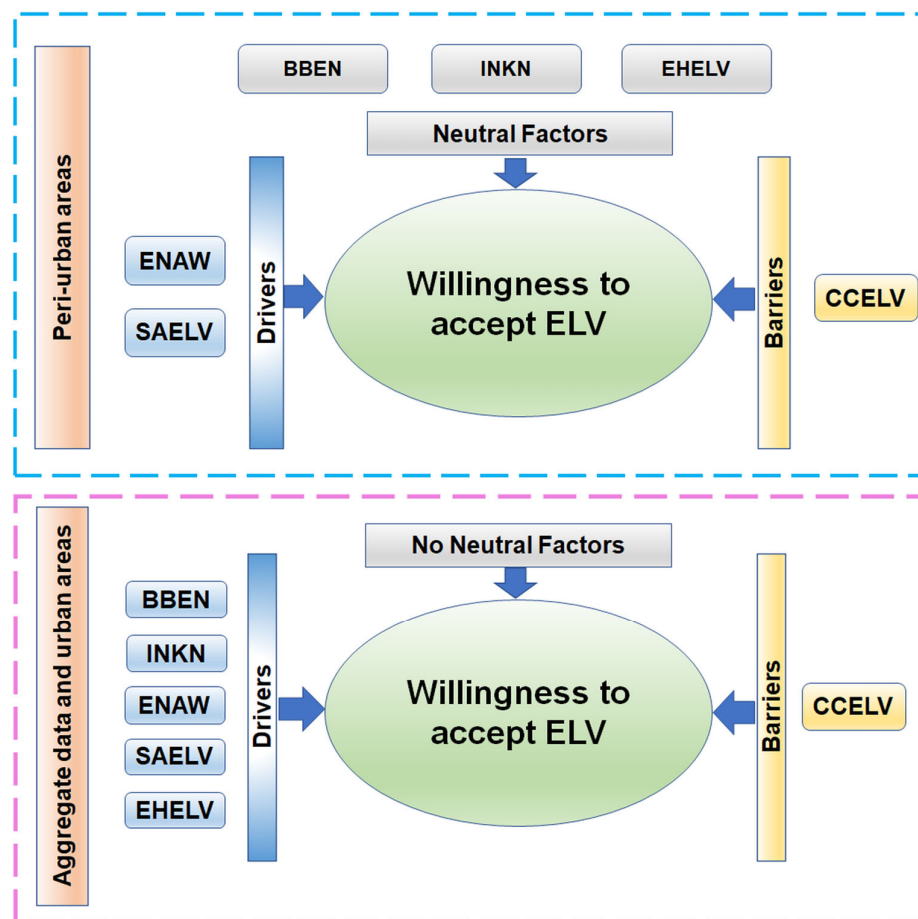

Figure 3. Image classifying the HIFs affecting the WAELV of individuals, presenting heterogeneous outcomes across urban and peri-urban areas. *Source:* authors' drawing based on PLS-SEQM results.

The empirical findings were used to classify BBEN, INKN, ENAW, SAELV, and EHELV as positive contributors to the WAELV of individuals in the aggregate data and urban areas. Nevertheless, BBEN, INKN, and EHELV imparted a neutral effect on WAELV in the case of peri-urban areas. On the contrary, the CCELV imparted negative contributions to the WAELV of individuals. Among the drivers of WAELV, SAELV was determined to be the strongest factor. However, BBEN was found to be the weakest driving force in this study (see Figure 2).

5. Conclusions and Policies

This research was an attempt to examine the HIFs impacting the WAELV of individuals in an IDM conceptual framework. For this purpose, we integrated novel HIFs such as the benefits for the built environment, knowledge about innovation, and the environmental and health benefits of ELVs into our conceptual framework to contribute to the extant literature on the WAELV of individuals. A PLS-SEQM empirical analysis was performed using survey-based data from urban and peri-urban areas of the Shandong province in China. The empirical findings were classified as follows: (1) Most of the HIFs contributed positively to individuals' WAELV and were classed as drivers. These factors included

the benefits for the built environment, knowledge about innovation, the environmental awareness aspect, the societal aspect of ELVs, and the environmental and health benefits of ELVs in the case of aggregate data and urban areas. (2) Only the HIF of the capital cost of ELVs appeared to be a barrier to the WAELV of individuals in the studied areas. (3) Contrariwise, in the peri-urban areas, the benefits for the built environment, knowledge about innovation, and the environmental and health benefits of ELVs proved to be neutral factors influencing the WAELV of individuals. This highlighted the disparity between the urban and peri-urban areas in terms of certain factors affecting the WAELV of individuals.

The policy recommendations are drawn as follows, based on key empirical findings.

Firstly, as the capital cost of ELVs was found to be a barrier to WAELV of individuals, a reduction in capital cost would help overcome this barrier and thus accelerate the willingness of those individuals to prefer such vehicles over traditional, fuel-based vehicles. Secondly, a clear disparity has been found between urban and peri-urban areas in terms of the effects of the benefits for the built environment, knowledge about innovation, and the environmental and health benefits of ELVs on the WAELV of individuals. Our study showed that urban individuals comprehend the benefits of ELVs for the built environment. Additionally, they understand the environmental health advantages of accepting ELVs, and have better knowledge of innovations. Therefore, these factors significantly and positively influence individuals from urban areas. However, individuals from the peri-urban areas stay neutral about these factors due to a lack of knowledge of innovation and less awareness of the environmental and health benefits. Thus, more knowledge regarding innovation and enhanced awareness about the environmental and health benefits and advantages for the built environment would help individuals from peri-urban areas to accept such vehicles more.

Though this research made substantial contributions to improve the understanding of ELV marketers, policymakers, and academic researchers, certain limitations need attention from scholars interested in working on the same subject matter. First, the data samples under analysis were confined to selected prefectural cities of the Shandong province of China, which could potentially limit the generalizability of the research findings. Therefore, future studies should conduct surveys on a broader spectrum to make the results more generalizable for better policy implications. Second, while conducting a comparative analysis between urban and peri-urban settings, the basic sociodemographic features were not controlled for in this study, which is a limitation of the SEQM technique. Thus, future research should accommodate those features by applying experimental design data tools such as propensity score matching or difference-in-difference methods to display more robust results. This limitation is critical because individuals in urban regions would be more qualified and better aware of the innovations and would thus have an enhanced probability of accepting innovative products like ELVs.

Data Availability Statement: The data used in this study will be made available at a suitable request.

Conflicts of Interest: Huang Jian and Chen Wei are employees of Era Co., Ltd., Taizhou 318020, Zhejiang, China. The paper reflects the views of the scientists, and not the company.

Abbreviations

AVEX: average variance extracted, BBEN: benefits for the built environment, CCELV: capital cost of electric vehicles, CNFA: confirmatory factor analysis, CRL: composite reliability, CVL: convergent validity, DVL: discriminant validity, ELV: electric vehicle, EHELV: environmental and health benefits of ELVs, ENAW: environmental awareness aspect, HIFs: heterogeneous influence factors, IDM: integrated decision making, INKN: knowledge about innovation, LTCs: latent components, PHIFs: path of coefficient of HIFs, PLS-SEQM: partial least square structural equation modeling, SAELV: societal aspect of ELVs, SREAV: square roots of the extracted average variance, UNVs: unobservable variables, VIFS: score of variance inflation factor, WAELV: willingness to accept ELVs.

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