

## Article

# Policy Instruments for the Improvement of Customers' Willingness to Purchase Electric Vehicles: A Case Study in Iran

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**Abstract:** Given the various advantages of electric vehicles compared to conventional gasoline vehicles in terms of energy efficiency and environmental pollution (among others), this paper studies the factors affecting customers' willingness to purchase electric vehicles. An integrated discrete choice and agent-based approach is applied to model the customers' choice for the valuation of electric vehicles based on the internal reference price. The agent-based model evaluates customers' preferences for a number of personal and vehicle attributes, according to which vehicle they chose. Data from 376 respondents are collected to estimate a random-parameter logit model where customers are asked to reveal their preferences about five attributes of electric vehicles, including travel range, top speed, charge cost, government incentives, and price. The role of social networks of customers and their threshold purchase price is also examined in the agent-based model. The scenario simulation results indicate that the allocation of government incentives for electric vehicles, decreasing electric vehicle/non-electric vehicle price gap, expanding electric vehicle travel range, increasing gasoline prices, and enhancing electric vehicle top speed stimulate electric vehicle market shares, respectively.

**Keywords:** agent-based model; discrete choice model; electric vehicles; market research; transport policy; willingness to pay



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## 1. Introduction

Nowadays, using low-consumption and/or clean fuel vehicles is becoming more and more important. Air pollution from fossil fuels, a critically serious threat to the environment, can be significantly reduced by using electric vehicles (EVs) (Throughout the paper, by EV we mean battery electric vehicle (BEV)). In this regard, people's attitudes toward the use of EVs have been positive for such reasons as the existence of a cognitive and emotional relationship between the potential buyer and the vehicle, the growth of public awareness about green environment initiatives, and the promotion of governmental incentive policies [1,2]. The development of the EVs market calls for a better understanding of customer behavior and driving styles, as well as improving the quality of EVs [3]. Since 2008, advances in design, battery technology, power grid management, concerns about oil prices, and the harsh environmental needs of the planet to reduce greenhouse gases have led to a major shift towards the production of EVs [4]. However, EVs have some obvious limitations compared to those fueled by gasoline, which are likely to affect transportation behavior in several ways. This includes, for instance, lack of long travel range capability

and a long battery charge [5]. Due to customers' concerns about the battery charge and the high price of EVs, their sales have not yet reached their targets. In its new scenario, EV30 @ 30, the International Energy Agency, predicts that by 2030 the market share for EVs will be 30 percent [6]. According to IHS Marketing Research Center, EVs will account for 15 to 35 percent of new vehicle sales by 2040 [7]. However, all of these predictions depend on increasing customer interest in purchasing this type of vehicle.

EVs are nowadays recommended for large cities in Iran, in particular due to a fast liberalization of gasoline prices, thereby sharply increasing urban air pollution caused by the country's daily use of 86 million gallons of gasoline [8]; the high cost of domestic production of gasoline together with import constraints; and finally, the old age of gasoline cars and insufficient substitution rates by new energy efficient ones. Article 44 of the Sixth Five-Year Development Plan Law urges the reduction of carbon emission in the transport sector. The replacement of old vehicles is also encouraged in article 46 of the Plan [9].

Now, the question is what kind of EV with what features to produce and how to stimulate customers' demand for EVs? These all call for a need for understanding customer's perceptions (including awareness, impressions, and opinions) about the comparative advantages of EVs. While the only EVs supplied in the Iranian car markets are those imported, the policymakers have developed a number of policy measures aimed at market expansion, including import tariff exemptions for hybrid cars as well as non-financial policy instruments (e.g., construction of EV charging points in large, polluted cities like Tehran and Mashhad).

There is, in fact, a kind of attitude-behavior gap in people's demand for EVs. There may be numerous causes for such a gap, including the lack of market options, mistrust due to no consumption experience, and high prices for sustainable products [10]. Therefore, recognizing the way customers accept the product calls for the prediction of their willingness to pay [11]. Several recent studies attempt to understand EVs' demand, penetration, and policy implications. Quarles et al. [12] conducted a public opinion questionnaire of 1426 Americans via an online Qualtrics survey in 2017. The simulation with statistical models predicts that the market share of hybrid-electric and plug-in hybrid vehicles will comprise over 40% of the private fleet by 2050, while battery-electric vehicles will rise to between 5% and 7%, and gasoline vehicle ownership will fall sharply. Of course, they state that the accuracy of their results will be influenced by several changing factors, including population age distribution, technological innovations, manufacturer and fleet operator pricing decisions, and social network effects. Dutta and Hwang [13] conducted a survey of 262 Taiwanese residents. The authors found that not only measurements of vehicle performance, namely safety, reliability, and range, but other factors, such as purchasing price, charging facility, and maintenance and battery cost, also influenced consumers' sustainable consumption intentions. Chen et al. [14] conducted a much larger and more internationally based survey of residents from Denmark, Finland, Iceland, Norway, and Sweden. They found that battery life and driving range were more important to conventional fuel vehicle owners than current and former EV owners. In return, former EV owners considered vehicle-to-grid capability and charging time more important than current EV and conventional car owners.

Alongside these studies, our paper identifies that the factors affecting customers' preferences for purchasing an EV are based on discrete choice experiments with realistic choice settings. In these settings, respondents choose which new vehicle to buy from two possible electric vehicle models and one non-electric vehicle with a wide variety of attributes, including travel range, price, and energy cost, among others. This allows us to estimate the stated preferences for cars and simulate the real market in an agent-based model (ABM) using data from the discrete choice model (DCM).

Section 2 of the paper reviews the literature on the subject. The research methodology is discussed in Section 3. Section 4 presents the estimation results, while the scenario simulation and validation are analyzed in Section 5. Section 6 concludes and discusses the paper.

## 2. Literature Review

### 2.1. Previous Studies on EVs Preferences

The previous studies may be classified into two parts: (1) those focusing on factors that might influence the behavior; and (2) those working on different approaches for the adoption rate prediction.

In part one, several effective factors on the behavior of buying an EV have been identified in many studies, a selected list of which is presented in Table 1. These factors may be divided into two categories; first, those related to individuals including socio-economic characteristics (gender, age, income, education level, and household composition), psychological factors (pro-environmental attitude, concern for battery, and innovativeness), spatial variables (charging capability, living in urban area, countries and regions) and car-related condition (current car condition, expected car condition); and second, those related to the vehicle itself, including financial attributes (purchase price and charge cost), technical attributes (travel range, charge duration, and top speed), infrastructure attributes (charging availability), and policy attributes (reduction/exemption of purchase tax, free parking, reduction of tolls, reduction/exemption of road tax, and reduction of purchase price).

**Table 1.** Factors affecting purchasing behavior.

Authors	Socio-Economic Variables	Psychological Factors	Spatial Variables	Car-Related Condition	Financial Attributes	Technical Attributes	Infrastructure Attributes	Policy Attributes
Noel et al. [15]	✓	✓	✓			✓		✓
Byun et al. [16]	✓			✓	✓			✓
Onat et al. [17]		✓	✓					✓
Noori and Tatari [18]	✓			✓	✓		✓	✓
Valeri et al. [19]	✓			✓	✓	✓		
Hidrue et al. [20]	✓	✓		✓	✓	✓		

In part two, many recent studies attempt to understand how customer preferences for such attributes as travel range, charge cost, and policy may shape the demand for EVs. Statistical models are utilized to discover this demand behavior. The most used models are the discrete choice and agent-based models. In most studies using DCM, questionnaires collect data on stated preferences to estimate the utility function for EVs within logit or probit models. On the other hand, in ABM, a market or system is modeled as a set of independent decision-making entities called agents. Agents have different individual characteristics including demography, behavioral rules, resources, level of information, and factors affecting behaviors [21]. Each agent individually evaluates its situation and makes decisions based on a set of rules [22]. A summary of the approaches used in previous studies is presented in Table 2.

While the literature on the adoption of EVs mostly utilizes DCM and ABM, a few studies reviewed here formulate integrated approaches as well. A pioneering contribution in this regard is Brown [27], who develops an agent-based mixed logit model to simulate EVs diffusion. The results show that government financial incentive availability leads to greater market shares. Shafiei et al. [28] also use a vehicle choice algorithm, the Multinomial Logit Model, and ABM to anticipate the market share of EVs in Iceland. Their results indicate that EVs will have the largest market share under a scenario containing high gasoline prices, low EV consumption taxes, and no worries regarding EV charging. Some studies also refer to integrated approaches, though in cases other than the vehicle industry. For instance, the importance of emerging patterns of market change and environmental conditions is confirmed by Araghi et al. [29], who study the diffusion of solar photovoltaic panels in the Netherlands. They provide a methodological framework by informing ABM with DCM. By analyzing the advantages and disadvantages of the choice models, Hörl et al. [30] study

the behavior of the passengers in selecting the transportation models by pairing discrete mode choice models and agent-based transport simulation with MATSim.

**Table 2.** Different approaches for the adoption rate prediction.

DCM		
Authors	Models	Results
Danielis et al. [23]	Multinomial logit Random parameter logit	Purchase price, fuel economy, driving range, charge time, free parking for EVs, and financial incentives affect the probability of buying EVs.
Nie et al. [24]	Multinomial logit Random parameter logit	Consumers preferred EVs with an extended range, a shorter charging time, a faster maximum speed, lower pollution emissions, lower fuel cost, and a lower price.
ABM		
Authors	Models	Results
Buchman et al. [25]	ABM and set of a business as usual (BAU) scenario	A combined package carbon tax on fuel, charging points, and direct subsidies affects the diffusion of EVs.
Klein et al. [26]	ABM simulation using choice-based conjoint data	EVs' charging time, range, and station density presumably cannibalize plug-in hybrid electric vehicle (PHEV) market shares. A government subsidy can initially promote PHEVs, but EVs will benefit later from that promotional effect.

## 2.2. Research Gap

Due to various agents affecting the EVs market, it is necessary to accurately identify and examine the agents' relationship. People's preferences change when they interact with different agents in the real world. The ABM approach has been employed to account for such a dynamic relationship and as a tool for market simulation. ABM hypothesizes that emergence phenomena is produced by agents making decisions and interacting with each other. On the other hand, ABM considers the interactions and connections between agents only in general terms. "The lack of data to calibrate the model is a common problem encountered in ABM. While theoretically accurate, they cannot be empirically sound if not fed with reliable data representing the true preferences of the agents. In general, this leads to the assignment of hypothetical assumed values to the attributes in order to study the emergence of collective phenomena in a bootstrapping fashion" [31].

Despite DCM and ABM, which have very different purposes and may be evaluated from different aspects of view, employing both DCM and ABM approaches simultaneously has many advantages: (i) DCM allows individuals to choose from a list of proposed sets for future consumption of goods [32]; (ii) ABM can better understand customers' behavior if preferences and attitudes are identified with DCM and estimated by utility functions within logit or probit models and, therefore, can provide an acceptable input source for the ABM [31,33]; and (iii) it is important to combine DCMs with ABMs to take advantage of their strengths while overcoming their weaknesses, because having good knowledge of customer behaviors and preferences—based on empirical data—is essential for the good performance of a model and for ensuring its predictive reliability [31]. However, identifying features and estimating agent preferences is a time-consuming and challenging issue.

Behavioral pricing is a relatively new approach to commodity pricing. Pricing for a product is determined by prospective customers' behavior. The formation and usage of reference prices are one of the areas of behavioral pricing research. Kalyanaram and Winer [34] believe that the customer's reference price is determined by the expected price of previous purchase experience and the present shopping environment. The reference price is divided into internal and external reference prices based on the source of the price information received. Kalyanaram and Little [35] point out that the internal reference price

is the price stored in the customer's memory from the previous buying process, whereas the external reference price is the price seen by customers in the purchasing environment.

While EVs are already in use in many countries, where the price may be easily derived by the so called "invisible hand" or market mechanism, it is difficult to work out the price in countries like Iran, where there are no EVs in use. Therefore, this research is a novel effort to extract the customers' utility and their willingness to pay for EVs by comparing the features of EVs with those of vehicles they own in the country of our study.

The purpose of this paper is to reveal customers' preferences for EVs and non-electric (gasoline/hybrid) vehicles (NEVs) using an internal reference price, with the goal of recommending suitable policy instruments to the government and automakers.

The research results can be useful for at least two reasons. First, identifying the attributes and how they affect demand will have a significant impact on providing the incentives needed to use EVs. Second, using the indicator of customers' willingness to pay for EVs and determining their sensitivity to the attributes of EVs can measure market potential for demand and evaluate the technology from customers' perspectives.

### 3. Research Methodology

As pointed out in the previous section, we have no choice but to apply a stated preference method in countries where there are no EVs in use. This method is ideal for eliciting monetary values. Contingent valuation (CV) and choice experiments (CE) are popular stated preference techniques. CE divides goods into attributes, where each attribute has different levels. The respondents are then presented with a series of option sets, including various combinations of attribute levels paired with a price attribute. This experimental design indirectly elicits information about respondents' exchange between payments and changes in the attributes of the commodities [36]. Figure 1 illustrates the methodological procedures of the study.

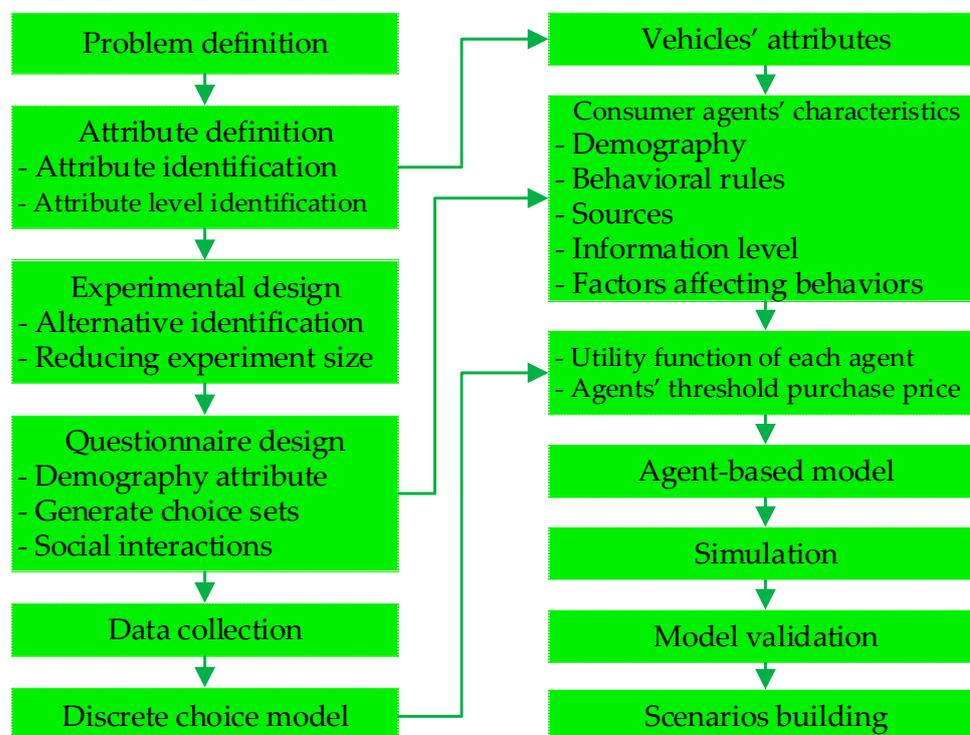


Figure 1. Research structure.

This approach allows customers/agents to evaluate the relative attractiveness of vehicles according to their attributes and construct a preferential order based on which they choose from different EVs and NEVs.

### 3.1. Formulation of the Model

The research begins with the identification of the EV attributes that motivate customers' willingness to pay. The second step is to identify the features or components of the car. These attributes should include all the components of the car. Based on the research background in Section 2, the six attributes of travel range, charge duration, top speed, charge cost, government incentives, and price are selected from the literature. Then, different levels are assigned to each of the attributes in order to make alternative attribute combinations for respondents to choose from. Alternative levels on all vehicle attributes other than price are chosen based on the features of the EVs currently available in the market (namely Renault Zoe, Renault Megane, Volkswagen ID.3, BMW ix3, and Mercedes EQS AMG) [37].

Questionnaires are distributed among a target group randomly chosen from potential buyers of NEVs (including 30 taxi drivers, 20 civil servants, 25 engineers, and 20 freelancers) in order to study their preferences and attitudes toward EVs. The reason for such a divergence in the social groups chosen is that they have different life and job styles, resulting in a variety of attitudes towards price, environmental pollution, and the travel range per day.

Members of the sample were examined for their driving habits and the price of the vehicle they are likely to pay in the future. This lets us control the vehicle design (interior and exterior decoration), size, and safety. To identify the vehicle price, both reservation and internal reference prices are used to calculate a single price. To do so, the internal reference price (the most preferred price for purchasing a NEV) is determined first. Then, by considering the higher configuration of the EV, a price that is higher than the internal reference price is set for the EV. This premium must be paid in order to enjoy the EV's advantages. The highest and lowest price that a buyer or seller is willing to buy or sell for is the reservation price.

The participants announced their willingness to pay for a vehicle in the range of 8 to 18 thousand dollars for respective attributes. As a result, we consider five prices, namely 8000, 10,000, 12,000, 14,000, and 18,000 dollars. The statistics on NEVs (namely Quik R, Peugeot 206, Samand LX, Hyundai Santa Fa, and BMW 5-series sorted by lowest to highest top speed) are collected from the respective car's homepage. The key attributes of the vehicles and their levels are summarized in Table 3.

**Table 3.** Vehicle attributes and corresponding levels.

Attributes	Vehicles	Levels	Number of Levels
Travel range (km)	EV (by one full battery)	315, 365, 450, 385, 565	5
	NEV (by one full tank fuel)	585, 780, 795, 750, 1150	5
Refueling duration	EV	20 min, 40 min, 1 h, 2 h, 4 h	5
	NEV	10 min, 15 min	2
Top speed (km/h)	EV	135, 150, 160, 180, 250	5
	NEV	160, 170, 185, 190, 250	5
Energy cost (US\$)	EV (Charge cost per kWh)	0.02, 0.025, 0.03, 0.04, 0.07	5
	NEV (Gasoline cost)	0.15, 0.3, 0.35	3
Government incentives	EV	Loan allocation, Removal of traffic restrictions, Tax removal and urban toll	3
	NEV	No government incentives	1
Price (US\$)	EV	8000, 10,000, 12,000, 14,000, 18,000	5
	NEV	5000, 7500, 9000, 12,000, 15,000	5

Reference: opinions of experts and group discussion.

The combination of all attributes and prices and their corresponding levels results in 9375 possible options for an EV and 750 possible options for a NEV. D-optimal design is

used to compute and present the optimal combinations of the attribute levels. “D-optimal design is constructed to minimize the overall variance of the predicted regression coefficient by maximizing the value of determinant of the information matrix” [38]. Applying a D-optimal algorithm in MATLAB software, eight pairs of optimal attributes set for EV option 1, EV option 2, and NEV are finally selected for our customer questionnaires, as is shown in Table 4.

**Table 4.** Alternative attribute sets are offered to customers in questionnaires.

Choice Sets	Vehicles	Travel Range	Refueling Duration	Top Speed	Energy Cost	Government Incentives	Price
Pair 1	EV option 1	315	2 h	135	0.02	Removal of traffic restrictions	8000
	EV option 2	565	20 min	250	0.04	Tax removal and urban toll	18,000
	NEV	795	10 min	185	0.15	No government incentives	9000
Pair 2	EV option 1	450	20 min	160	0.025	Loan allocation	12,000
	EV option 2	455	40 min	180	0.025	Removal of traffic restrictions	14,000
	NEV	1150	10 min	250	0.35	No government incentives	15,000
Pair 3	EV option 1	455	40 min	180	0.07	Loan allocation	14,000
	EV option 2	365	4 h	150	0.03	Loan allocation	10,000
	NEV	585	5 min	160	0.15	No government incentives	5000
Pair 4	EV option 1	450	1 h	160	0.025	Loan allocation	12,000
	EV option 2	565	20 min	250	0.07	Tax removal and urban toll	18,000
	NEV	795	10 min	185	0.3	No government incentives	9000
Pair 5	EV option 1	455	40 min	180	0.02	Tax removal and urban toll	14,000
	EV option 2	565	1 h	250	0.07	Removal of traffic restrictions	18,000
	NEV	1150	5 min	250	0.35	No government incentives	15,000
Pair 6	EV option 1	450	2 h	160	0.03	Loan allocation	12,000
	EV option 2	565	40 min	250	0.02	Tax removal and urban toll	18,000
	NEV	780	10 min	170	0.15	No government incentives	7500
Pair 7	EV option 1	565	20 min	250	0.04	Removal of traffic restrictions	18,000
	EV option 2	455	20 min	180	0.03	Tax removal and urban toll	14,000
	NEV	750	5 min	190	0.3	No government incentives	12,000
Pair 8	EV option 1	450	20 min	160	0.03	Tax removal and urban toll	12,000
	EV option 2	565	4 h	250	0.025	Loan allocation	18,000
	NEV	780	5 min	170	0.3	No government incentives	7500

Reference: research results using MATLAB.

### 3.2. Questionnaire Design & Data Collection

The questionnaire consists of three sections. First, respondents are asked about their demographic characteristics, including gender, age, educational level, occupation, marital status, and income range.

The second section of the questionnaire targeted respondent preferences for various vehicles attributes. For instance, one of the eight choice sets offered to the respondents is illustrated in Table 5.

**Table 5.** Sample vehicles choice questionnaire.

Attributes	EV Option 1	EV Option 2	NEV
Travel range (km)	315	565	795
Refueling duration	2 h	20 min	10 min
Top speed (km/h)	135	250	185
Energy cost (US\$)	0.02	0.04	0.15
Government incentives	Removal of traffic restrictions	Tax removal and urban toll	No government incentives
Price (US\$)	8000	18,000	9000
<b>The preferred choice between these vehicles is according to the above attributes.</b>			

Questions in the third section of the questionnaire refer to social interactions. A five-point Likert scale (never (1), rarely (2), usually (3), strongly (4), and very strongly (5)) is used. The statements are designed to analyze the social network and relationship between customer agents in the ABM—the details of which are demonstrated in Table 6.

**Table 6.** The statements reveal respondents' social interactions.

<b>Statement 1</b>	I usually recommend the car I buy to others.
<b>Statement 2</b>	I usually talk to my friends a lot about the price and features of the appropriate car.
<b>Statement 3</b>	I listen to people's advice to buy a car.
<b>Statement 4</b>	I have full knowledge of electric cars.

The study's statistical population is potential buyers of gasoline, hybrid, plug-in, or electric cars in two large cities, namely Tehran and Mashhad. The sample includes those who have already bought or intended to buy a car in the last six months. Data is collected from 376 customers who were randomly selected from 140 automobile stores in Tehran and 75 in Mashhad. It should be noted that the population census data officially reported by the Statistical Center of Iran is indicative of less than a 0.003% difference between the demographic characteristics of people in the two cities under study [39].

### 3.3. Discrete Choice Model

McFadden's discrete choice is based on Thurstone's random utility model [40,41]. Random utility theory assumes that an individual behaves rationally and chooses the option that has the highest level of utility. As all factors affecting the actual utility of individuals are not observable and the necessary and sufficient information about customer choice is not available, the utility function in the random utility model is a conditional indirect utility function (subject to option choice).

After identifying the attributes of the EV and the random utility model, the conditional indirect utility (generally assumed to have a linear form) can be written as Equation (1) below.

$$U_{iq} = \beta_{0iq} + \sum_k \sum_i \sum_q \beta_{kqiq} X_{kqiq} + \alpha_{iq} \text{Price}_{iq} + \sum_n \sum_i \sum_q \gamma_{niq} S_{niq} + \varepsilon_{iq} \quad (1)$$

where  $U$  is the utility gain by customers;  $X$  is the attributes of the EV ( $k = 1, 2, 3, 4, 5$ ); price is the price of the EV;  $S$  refers to the demographic variables;  $i$  is vehicle options (choosing a value of 1 and 2 for two EVs with different sets of attributes, and 3 for NEV);  $q$  represents the customers (here 376);  $k$  represents the EV attribute; and  $n$  represents personality traits of individuals.  $\alpha$ ,  $\beta$ , and  $\gamma$  are the explanatory variable parameters to be estimated.  $\varepsilon_{iq}$  is a stochastic component distributed independently and uniformly with an infinite value. This distribution, known as the Gumbel distribution, is a special case of the generalized limit value distribution, which is described by a scale parameter  $\mu$  and a location parameter  $\delta$  in practice.

Depending on the assumptions made for the shape of the random component distribution, different possible choice models can be considered for Equation (1). This paper uses the random-parameter logit model to find heterogeneity in people's behavior. Heterogeneity of data is inevitable in the real world. A random-parameter logit model is then used to account for data heterogeneity [42]. The stochastic component of the model  $\varepsilon_{iq}$  in the mixed logit model consists of two parts. In the first part, log-normal, uniform, triangular, gamma, or any other distribution can be used, and the second part, like the standard logit model, consists of a limited amount of distribution with independent and identical distribution, so it has fewer limiting assumptions. Given its capabilities, this model is expected to have more predictive power. By considering the appropriate distributions for the characteristics of the coefficients in the utility function, the behavior of different models with random utility can be approximated [43]. Based on this, as an integral of the logit model, the

random coefficients model is defined on the density function of the  $\theta$  parameters, shown as Equation (2), is the probability of a mixed logit.

$$P_i = \int \frac{\exp\left(\sum_k \sum_i \sum_q \beta_{kiq} X_{kiq} + \alpha_{iq} \text{Price}_{iq} + \sum_n \sum_i \sum_q \gamma_{niq} S_{niq}\right)}{\sum_{j=1}^J \exp\left(\sum_k \sum_i \sum_j \beta_{kij} X_{kij} + \alpha_{ij} \text{Price}_{ij} + \sum_n \sum_i \sum_j \gamma_{nij} S_{nij}\right)} f(\theta | \omega) d\theta. \quad (2)$$

where  $\theta$  refers to  $\beta$ ,  $\alpha$ , and  $\gamma$ ;  $\omega$  refers to the distribution parameter (mean and standard deviation) assigned to the coefficients. This way, it is possible to calculate the distribution parameters by considering the appropriate distribution for the coefficients. Normal-distributed random coefficients are used to estimate the coefficients of  $\theta$  to further improve the logarithmic value of the likelihood function and to use the mixed logit model in the agent-based model.

Mixed logit is well suited to simulation methods for estimation [44]. The probability of a mixed logit in Equation (2) can be approximated using a Monte Carlo integration approach, as in Equation (3).

$$\check{P}_i = \frac{1}{R} \sum_{r=1}^R \frac{\exp\left(\sum_k \sum_i \sum_q \beta_{kiq}^{(r)} X_{kiq} + \alpha_{iq}^{(r)} \text{Price}_{iq} + \sum_n \sum_i \sum_q \gamma_{niq}^{(r)} S_{niq}\right)}{\sum_{j=1}^J \exp\left(\sum_k \sum_i \sum_j \beta_{kij}^{(r)} X_{kij} + \alpha_{ij}^{(r)} \text{Price}_{ij} + \sum_n \sum_i \sum_j \gamma_{nij}^{(r)} S_{nij}\right)} \quad (3)$$

where  $R$  refers to the number of draws;  $\check{P}_i$  is an unbiased estimator of  $P_i$  by construction; and  $\beta_{kiq}^{(r)}$ ,  $\alpha_{iq}^{(r)}$ ,  $\gamma_{niq}^{(r)}$  represents random draw  $r \in \{1, \dots, R\}$  from the normal density  $f(\theta|\omega)$ .

#### 4. Survey

The demographic statistical description of our sample customers and their social communication structure (as classified in Table 5) are illustrated by Figure 2 and Table 7, respectively.

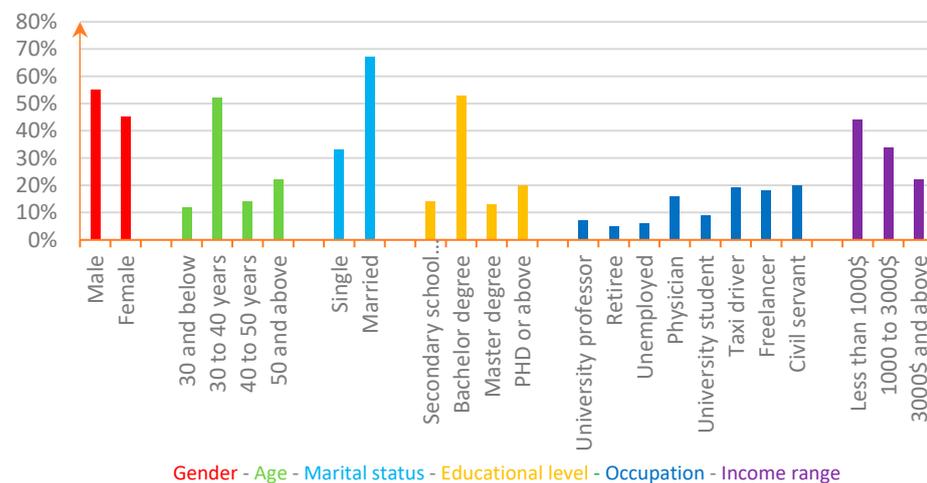


Figure 2. Demographic characteristics of the respondents (n = 376).

Table 7. Status of social communication.

Statements	Weighted Average Score
Statement 1 I usually recommend the car I buy to others.	4.91
Statement 2 I usually talk to my friends a lot about the price and features of the appropriate car.	4.37
Statement 3 I listen to people’s advice to buy a car.	3.75
Statement 4 I have full knowledge of electric cars.	3.41
<b>Total Average</b>	<b>4.11</b>

A total weighted average of 4.11 out of 5 is indicative of a high social interaction of respondents.

According to the estimation results of the mixed logit choice model, preferences vary from individual to individual with respect to energy cost and refueling duration; while all individuals of the sample have constant preferences with respect to price, government incentives, travel range, and top speed.

According to the preliminary results, the estimated parameter of refueling duration is statistically insignificant. Therefore, the refueling duration variable is excluded from the model. The final estimation result is demonstrated by Table 8.

**Table 8.** Customers' choice estimation results.

Attributes	Vehicles	Coefficient	Std. Error	P >  Z
Price	EV	−0.0066	0.0049	0.000
	NEV	−0.0041	0.0074	0.005
Travel range	EV	0.0087	0.0094	0.000
	NEV	0.0128	0.0071	0.002
Top speed	EV	0.0086	0.0039	0.007
	NEV	0.0119	0.0096	0.091
Government incentives	EV	0.0251	0.0057	0.047
	NEV	0.0072	0.0037	0.000
Energy cost	EV	−0.0069 (0.0566)	0.0063 (0.0031)	0.001
	NEV	−0.0059 (0.0111)	0.0041 (0.0045)	0.014
Log simulated likelihood			−5702.135	
Number of observations			9024	
Wald chi2 (2)			104.77	
Prob > Chi2			0.0000	

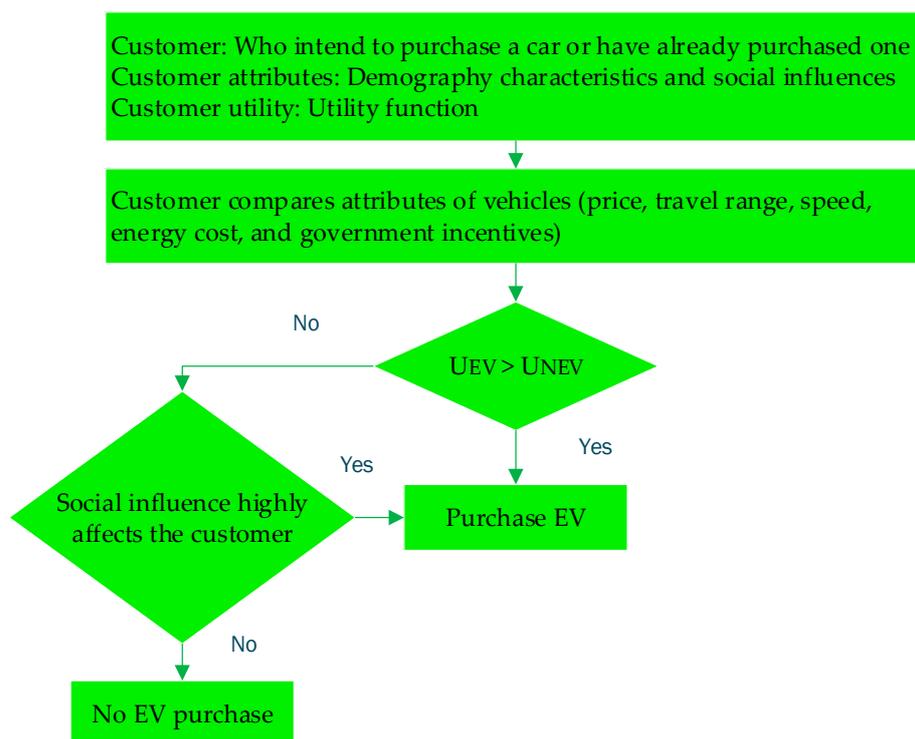
Numbers in parentheses are standard deviation.

The estimated fixed coefficients (of price, travel range, top speed, and government incentives) are all statistically significant at a probability level of 10% or below, which represents the probability of preferring an EV in response to changes in respective attributes. The estimated mean of the normally-distributed random coefficients on energy cost is −0.0069, with a standard deviation of 0.0566, indicating heterogeneity across sample individuals.

## 5. Agent-Based Model

### 5.1. Vehicle Choice Algorithm

Figure 3 presents an algorithm through which customers make their choice. They make decisions based on demographic characteristics and vehicle attributes. The customer's decision to purchase EVs may also be affected by social influences (including marketing, advertisement, and the word-of-mouth opinion of current owners of EVs).



**Figure 3.** Vehicle choice algorithm.

The utility of each customer agent for the vehicle is determined by the following algorithm:

If  $U_{EV} \geq TR$  Then  $U = U_{EV}$  Else  $U \neq U_{EV}$   
 If  $U_{NEV} \geq TR$  Then  $U = U_{NEV}$  Else  $U \neq U_{NEV}$   
 If  $U_{EV} \geq TR$  &  $U_{NEV} \geq TR$  Then  $U = \text{Max} \{U_{EV}, U_{NEV}\}$   
 $0 \leq U_{EV}, U_{NEV} \leq 1$   $TR = 0.35$  (Research result)

Where  $U$  is the utility gain,  $U_{EV}$  is the utility gain from EV (Equation (1)),  $U_{NEV}$  is the utility gain from NEV, and  $TR$  refers to the threshold purchase price. The agent compares the value of satisfaction from an EV with its respective threshold purchasing price. If the value of satisfaction exceeds that threshold, the agent chooses EV; otherwise, he/she does not buy an EV. The threshold purchasing price or the internal reference price is the most preferred price for purchasing a NEV.

### 5.2. Social Network

To study a large-scale social network, one should identify its (community or modular) subnets. A “community” may be defined as a collection of individuals who share a common aim, interest, or likewise connections [45]. In Iran, in particular, social networks are very strong, such that any news (good or bad) is promptly diffused among all members of the community.

Each customer agent has two types of interaction: (i) interaction with vehicle regarding its price, top speed, travel range, energy cost, and government incentives; and (ii) interaction with other customer agents (social influence of each agent on another). To measure the latter, a social network approach has been applied. A randomly generated social network does not represent the structure of real-world networks, so a preferential attachment process is applied in which each customer agent knows others.

Agents differ in choice alternatives and their interactions with each other. The dynamics of the agents in the social network are described by preferential attachment, where the preferred behavior of the agents is formed by their interaction with other agents and by obtaining more information [46]. A new connection is established over time between the agents, resulting in a preferential attachment and creating new links in the communica-

tion chain. In a social network based on preferential attachment, a few nodes have many links, and new nodes connect with multiple links [47]. A social network with preferential attachment is one in which new agents (customers) join the network by connecting to those agents with high levels of connectedness. Net Logo coding is used to design such a social network.

### 5.3. Simulation

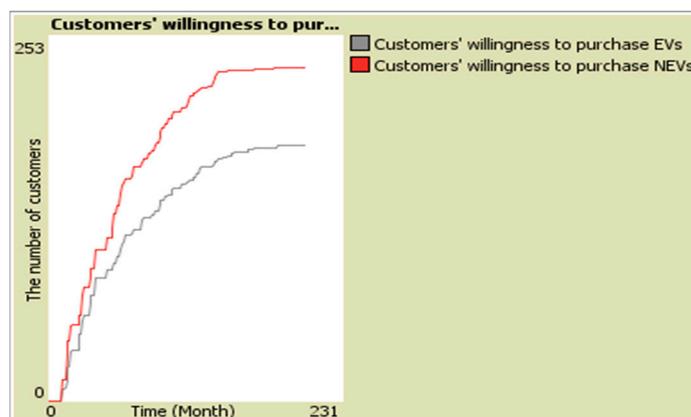
The agent-based model is formulated using Net Logo 6.1.0. in order to examine the agents' attitudes towards the five attributes of vehicles. Given the importance of income in customers' preference construction, they are divided into three income categories: high, middle, and low. The respective coefficient of variables for each group are assigned as a normal random value with an interval  $[\mu - \delta, \mu + \delta]$ , where  $\mu$  and  $\delta$  are the mean and standard deviation, respectively. The results of the logit estimation are as depicted in Table 9.

**Table 9.** Customers' sensitivity by income group.

Income Group Attributes	High	Middle	Low
<b>The Mean of Beta Coefficients</b>			
Price	−0.0021 (0.0167)	−0.0077 (0.0619)	−0.0068 (0.0093)
Top speed	0.0013 (0.0095)	0.0897 (0.0214)	0.0767 (0.0228)
Energy cost	−0.0214 (0.0037)	−0.0041 (0.0071)	−0.0085 (0.0056)
Travel range	0.0916 (0.0271)	0.0011(0.0012)	0.0285(0.0108)
Government incentives	0.0671 (0.0813)	0.01708 (0.0057)	0.0075 (0.0091)
Number of observations	3960	3072	1992
Log simulated likelihood	−301.0409	−231.7124	−521.9007
Wald chi2 (2)	2.92	12.35	37.33
Prob > Chi2	0.0000	0.0000	0.003

Numbers in parentheses are standard deviation. Source: estimation results.

The results of customers' choice estimation and the sensitivity of customer behavior to each of the vehicles' attributes by income group (as in Tables 8 and 9) are used in the ABM. Figure 4 is indicative of a steadily increasing pattern in the willingness to purchase EVs.



**Figure 4.** Image of the simulated market in Net Logo.

### 5.4. Model Verification and Validation

There are three steps to verify the model results [48]: (i) The conceptual design and the implemented model are first documented; (ii) next, the code of the model is tested and the required statistical meaningfulness of the parameters is examined; and finally (iii), the

model functions are examined to ensure it operates as expected. For instance, an extreme value test is done to check if no agent is willing to purchase when the threshold indicator is set to 1, otherwise with a threshold level of 0, all agents purchase quickly, and the purchase curve moves upwards exponentially. Also, relative value testing is employed in order to ensure the conformity of results with the literature review.

In order to ensure model validation, we examined customer behavior in the real world according to behavioral economics assumptions and theories. According to neoclassical economics' hypotheses, individuals maximize utility or short-term personal gain. Richard Thaler, however, argues that cognitive abilities, self-control, and motivation can vary significantly across different individuals [49]. People make decisions in a world with asymmetric knowledge and information, the inability to manage personal habits, and specific social concerns. As a result, to simulate the vehicle market in ABM, we ensured that elements as well as processes and patterns of the implemented model correspond to the real world by employing a stochastic sampling approach. As a result, the model's output may be claimed to reflect the expected behavior in the real world. Given that Iranian customers only have a mental image of an EV, we employed the principles of behavioral pricing, internal reference pricing, and reserve pricing to ensure the accuracy of EV pricing. Customer agent data are collected from a representative sample of society using a discrete choice questionnaire. In the real world, individuals are not homogeneous in their sensitivity to vehicle features. With this in mind, the data is processed using the Monte Carlo simulation method with random parameter logit modeling. Given this, the operational model's input is calibrated using real-world data. A validation process is used that combines specific "face validation techniques" with statistical methods (sensitivity analysis and calibration of parameters), the results of which are available from the authors upon request.

### 5.5. Scenario Building

The main question is how a willingness to purchase EVs could be motivated by intervening instruments. Different scenarios for the price, energy cost, government incentives, travel range, and top speed are considered based on experts' opinions.

#### 5.5.1. Scenario 1: EV Price

The production cost of an EV is twice as much as a currently produced gasoline car with similar attributes [50]. This scenario, however, allows a 10-percent drop in the EV-NEV price gap as a result of cost efficiencies due to returns to scale and technology learning in time.

#### 5.5.2. Scenario 2: NEVs Energy Costs

The customer price of gasoline is \$0.15 a liter at the moment. This scenario considers a 10-percent rise in petrol price each year. This scenario is also a reasonable one in light of extreme sanctions and the government's willingness to finance its budget deficit through higher petrol prices.

#### 5.5.3. Scenario 3: EVs Government Incentives

In this scenario, the government allocates a subsidy equivalent to 20-percent of EV prices in order to encourage customers to purchase EVs rather than NEVs. This subsidy might be through different types, i.e., directly through customer tax cuts and imports tariff reductions for EVs and indirectly by increasing customer tax and imports tariff for NEVs.

#### 5.5.4. Scenario 4: EVs Travel Range

Recent technological advances are going to enable producers to extend the travel range of EVs to about 400 km on a single charge in the near future [51]. This scenario, therefore, considers a 30-percent increase in travel range.

### 5.5.5. Scenario 5: EVs Top Speed

The same argument as discussed for scenario 4 above holds for considering a 30-percent increase in the top speed of EVs.

Figure 5 shows the market share of EVs as a result of implementing each scenario over a period of 10 years from 2022 to 2032.

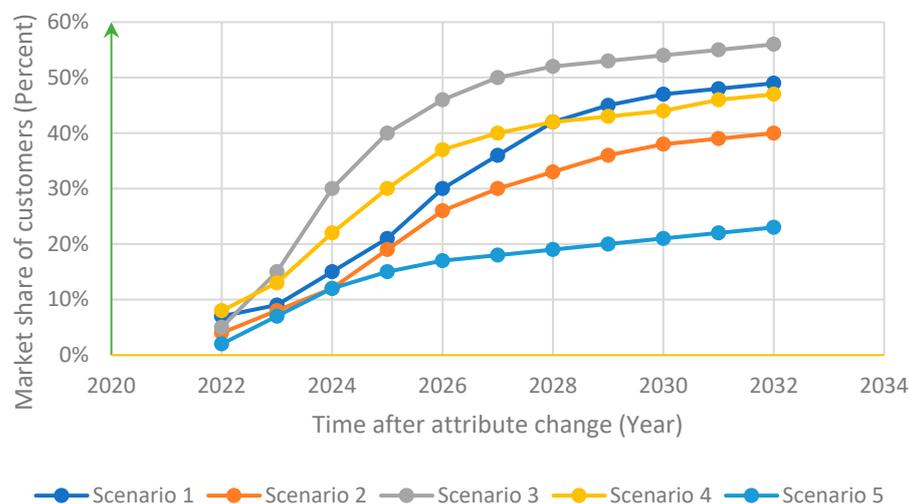


Figure 5. EV market share by scenarios.

## 6. Conclusions and Discussion

An agent-based model is applied to study the willingness to purchase electric vehicles. The results indicated that there is a heterogeneity of willingness to purchase NEVs and EVs. Five vehicle attributes have proved to have a significant effect on the willingness to purchase an EV in a mixed logit choice model. Applying the information derived from DCM in ABM, different scenarios on vehicle price, energy price, top speed, travel range, and government incentives are considered. The scenario priorities, in terms of their effectiveness in encouraging the purchase of EVs over a 10-year period after implementation, are the allocation of government incentives for EVs (56%), decreasing the EVs-NEVs price gap (49%), increasing EV travel range (47%), increasing gasoline prices (40%), and enhancing EV top speed (23%).

Given the effectiveness of government incentives, the government is recommended to follow incentive policies aimed at encouraging the use of clean fuel vehicles. This may include further construction of charging stations and providing car and battery manufacturers with low-cost financial support. The government budget is also recommended to target the purchase of EVs instead of NEVs for its own uses. Large and coordinated car purchases (e.g., taxi fleet) can also guarantee the minimum demand required for a fruitful start to the EV industry. The government owned broadcasting system may also play a crucial role in directing people's demand towards the EV market. The issue of education about electric mobility, which can help influence the public's approach to electric cars, is essential. Pollák et al. [52] find that changing people's mindset towards EVs is a big challenge to market development. Also, Turoń et al. [53] declare that each form of dissemination of knowledge using appropriate educational methods in the field of electric mobility (e.g., from the classic methods as lectures and working with books to new educational solutions like e-learning) could raise public awareness about the advantages of EVs. Similarly, our findings about the effect of social networks calls for the need to encourage EV consumption instruments through education systems to enhance people's awareness of sustainable transport advantages.

### 6.1. Comparative Analysis of the Results

A number of studies such as Brown utilize an agent-based mixed logit models to study the EV markets [27]. Comparing our results with those of other studies is proof of the validity of our study. Eggers and Eggers [54] and Brown conclude that a low price is the main source of competitive advantage for EVs, followed by travel range and financial incentives during the early years. Noori and Tatari [18] and Danielis et al. [23] also argue that government subsidies play an important role in the willingness to purchase EVs. Besides, according to Noori and Tatari [18], increasing the travel range or speed of EVs has little impact compared to other financial-based scenarios. Shafiei et al. [28] suggest increases in gasoline prices, followed by decreases in EV prices, which would bring considerable market shares for EVs. In contrast with this article, Byun et al. [16] and Hidrue et al. [20] conclude that drivers prefer shorter charging times, as respondents were willing to pay extra to reduce the charging time. One possible reason is that most respondents have not actually been faced with the problem of long charging times in the real world, as most of them have not experienced owning an EV. Similar to our results, however, they suggest that the government should build a charging infrastructure to encourage the use of electric vehicles.

This study, while confirming the result of other studies, provides an intervention policy package tailored for Iranian car industry policymakers.

### 6.2. Research Suggestions

We faced a number of limitations in this research. First, as the statistical data is collected from customers in two large cities, Tehran and Mashhad, the results may be generalized to the whole of Iranian cities only with due care. Of course, the results of the study may be generalized to other Iranian megacities like Isfahan, Karaj, Shiraz, Tabriz, Qom, and Ahwaz, which have populations of more than 1 million (totally more than one fourth of the country's population) and where there are a sufficient number of charging points and high potential demand for EVs. Second, as there is no active market for EVs in Iran, we were left with no option but to apply a DCM approach to identify customer preferences. One, however, may employ other approaches like that of Kotler [55], which is based on a Stimulus-Response Model (SRM), to provide a better understanding of customers' buying behavior.

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## References

1. Giansoldati, M.; Rotaris, L.; Scorrano, M.; Danielis, R. Does electric car knowledge influence car choice? evidence from a hybrid choice model. *Res. Transp. Econ.* **2020**, *80*, 100826. [CrossRef]
2. Heinicke, M.; Wagenhaus, G. Sustainability in the car-based mobility: The case of the electric vehicle Editha. *Int. J. Energy Energy Sect. Manag.* **2015**, *9*, 105–119. [CrossRef]
3. Hu, K.; Wu, J.; Liu, M. Exploring the energy efficiency of electric vehicles with driving behavioral data from a field test and questionnaire. *J. Adv. Transp.* **2018**, *2018*, 1–14. [CrossRef]
4. Cauwer, C.D.; Mierlo, J.V.; Coosemans, T. Energy consumption prediction for electric vehicles based on real-world data. *Energies* **2015**, *8*, 8573–8593. [CrossRef]
5. Jensen, A.F.; Mabit, S.L. The use of electric vehicles: A case study on adding an electric car to a household. *Transp. Res. Part A Policy Pract.* **2017**, *106*, 89–99. [CrossRef]
6. International Energy Agency (IEA). Global EV Outlook. 2019. Available online: <https://www.iea.org/reports/global-ev-outlook-2019> (accessed on 1 May 2019).
7. IHS Predicts EV Sales Explosion. 2016. Available online: <https://www.globalfleet.com/en/safety-environment/global/article/ihs-predicts-ev-sales-explosion?a=THA13&curl=1> (accessed on 12 December 2016).
8. TEHRAN TIMES. 2020. Available online: <https://www.tehrantimes.com/news/470091/Average-daily-gasoline-consumption-stands-at-86m-liters> (accessed on 13 February 2022).
9. Sixth Five-Year Development (2016–2021). Available online: <https://policy.asiapacificenergy.org/node/3671> (accessed on 10 April 2017).
10. Martin, D.M.; Väistö, T. Reducing the attitude-behavior gap in sustainable consumption: A theoretical proposition and the American electric vehicle market. *Mark. A Sustain. Soc. (Rev. Mark. Res.)* **2016**, *13*, 193–213. [CrossRef]
11. Daziano, R.A.; Sarrias, M.; Leard, B. Are customers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transp. Res. Part C Emerg. Technol.* **2017**, *78*, 150–164. [CrossRef]
12. Quarles, N.; Kockelman, K.M.; Lee, J. America’s fleet evolution in an automated future. *Res. Transp. Econ.* **2021**, *90*, 101107. [CrossRef]
13. Dutta, B.; Hwang, H.-G. Consumers purchase intentions of green electric vehicles: The influence of consumers technological and environmental considerations. *Sustainability* **2021**, *13*, 12025. [CrossRef]
14. Chen, C.F.; Rubans, G.Z.D.; Noel, L.; Kester, J.; Sovacool, B.K. Assessing the socio-demographic, technical, economic, and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. *Renew. Sustain. Energy Rev.* **2020**, *121*, 109692. [CrossRef]
15. Noel, L.; Rubans, G.Z.D.; Sovacool, B.K.; Kester, J. Fear and loathing of electric vehicles: The reactionary rhetoric of range anxiety. *Energy Res. Soc. Sci.* **2019**, *48*, 96–107. [CrossRef]
16. Byun, H.; Shin, J.; Lee, C.Y. Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. *Energy* **2017**, *144*, 312–321. [CrossRef]
17. Onat, N.C.; Noori, M.; Kucukvar, M.; Zhao, Y.; Tatari, O.; Chester, M. Exploring the suitability of electric vehicles in the United States. *Energy* **2017**, *121*, 631–642. [CrossRef]
18. Noori, M.; Tatari, O. Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy* **2015**, *96*, 215–230. [CrossRef]
19. Valeri, E.; Danielis, R.; Nassiri, H. Simulating the market penetration of cars with alternative fuel powers technologies in Italy. *Transp. Policy* **2015**, *37*, 44–56. [CrossRef]
20. Hidrue, M.K.; Parsons, G.R.; Kempton, W.; Gardner, M.P. Willingness to pay for electric vehicles and their attributes. *Resour. Energy Econ.* **2011**, *33*, 686–705. [CrossRef]
21. Macal, M.J.; North, C.M. Tutorial on agent-based modeling and simulation. *J. Simul.* **2010**, *4*, 151–162. [CrossRef]
22. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci. USA* **2002**, *99* (Suppl. 3), 7280–7287. [CrossRef]
23. Danielis, R.; Rotaris, L.; Giansoldati, M.; Scorrano, M. Drivers’ preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake. *Transp. Res. Part A Policy Pract.* **2020**, *137*, 79–94. [CrossRef]
24. Nie, Y.; Wang, E.; Guo, Q.; Shen, J. Examining Shanghai customer preferences for electric vehicles and their attributes. *Sustainability* **2018**, *10*, 2036. [CrossRef]
25. Buchman, T.; Wolf, P.; Fidaschekrain, S. Stimulating E-Mobility diffusion in Germany (EMOSIM): An agent-based simulation approach. *Energies* **2021**, *14*, 656. [CrossRef]
26. Klein, M.; Lüpke, L.; Günther, M. Home charging and electric vehicle diffusion: Agent-based simulation using choice-based conjoint data. *Transp. Res. Part D Transp. Environ.* **2020**, *88*, 102475. [CrossRef]
27. Brown, M. Catching the PHEVer: Simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. *J. Artif. Soc. Soc. Simul.* **2013**, *16*, 1–5. [CrossRef]
28. Shafiei, E.; Thorkelsson, H.; Ásgeirsson, E.I.; Davidsdottir, B.; Roberto, M.; Stefansson, H. An agent-based modeling approach to predict the evolution of the market share of electric vehicles: A case study from Iceland. *Technol. Forecast. Soc. Chang.* **2012**, *79*, 1638–1653. [CrossRef]

29. Araghi, Y.; Lee, E.P.; Bollinger, A. Informing agent-based models with discrete choice analysis: Diffusion of solar PV in the Netherlands. In Proceedings of Social Simulation Conference, Barcelona, Spain, 1–5 September 2014.
30. Hörl, S.; Balac, M.; Axhausen, K.W. Pairing discrete mode choice models and agent-based transport simulation with MAT-Sim. In Proceedings of the 98th Annual Meeting of the Transportation Research Board (TRB 2019), Washington, DC, USA, 13–17 January 2019. [CrossRef]
31. Pira, M.L.; Marcucci, E.; Gatta, V.; Inturri, G.; Ignaccolo, M.; Pluchino, A. Integrating discrete choice models and agent-based models for ex ante evaluation of stakeholder policy acceptability in urban freight transport. *Res. Transp. Econ.* **2017**, *64*, 13–25. [CrossRef]
32. Bateman, I.J.; Carson, R.; Hanemann, M. *Economic Valuation with Stated Preference Techniques: A Manual*; Edward Elgar Publishing: Cheltenham, UK, 2004. [CrossRef]
33. Dia, H. An agent-based approach to modeling driver route choice behavior under the influence of real-time information. *Transp. Res. Part C Emerg. Technol.* **2002**, *10*, 331–349. [CrossRef]
34. Kalyanaram, G.; Winer, R.S. Empirical generalizations from reference price research. *Mark. Sci.* **1995**, *14*, 161. [CrossRef]
35. Kalyanaram, G.; Little, J.D.C. An empirical analysis of latitude of price acceptance in consumer package goods. *J. Consum. Res.* **1994**, *21*, 408–418. [CrossRef]
36. Hensher, D.A.; Rose, J.M.; Greene, W.H. *Applied Choice Analysis: A Primer*; Cambridge University Press: Cambridge, UK, 2005; ISBN 9781107092648.
37. EV Database: Compare Electric Vehicles. 2022. Available online: <http://ev-database.org> (accessed on 10 May 2022).
38. Esbensen, K.H.; Guyot, D.; Westad, F.; Houmoller, L.P. *Multivariate Data Analysis: In Practice: An Introduction to Multivariate Data Analysis and Experimental Design*, 5th ed.; CAMO AS: Oslo, Norway, 2002; ISBN 8299333032.
39. Statistical Center of Iran. 2022. Available online: <http://www.amar.org.ir> (accessed on 8 May 2022).
40. McFadden, D. Conditional logit analysis of qualitative choice behavior. In *Frontiers in Econometrics*; Zarembka, P., Ed.; Academic Press: Cambridge, MA, USA, 1974.
41. Thurstone, L.L. A law of comparative judgment. *Psychol. Rev.* **1927**, *34*, 273–286. [CrossRef]
42. Rezaei, A.; Puckett, S.M.; Nassiri, H. Heterogeneity in preferences of air travel itinerary in a low-frequency market. *Transp. Res. Rec. J. Transp. Res. Board* **2011**, *2214*, 10–19. [CrossRef]
43. Cirillo, C.; Hetrakul, P. Continuous random coefficient logit models: A comparison of parametric and non-parametric methods to estimate individual preferences over cybernetic transportation systems. In Proceedings of the Transportation Research Board 89th Annual Meeting, Washington, DC, USA, 10–14 January 2010.
44. Train, K. *Discrete Choice Methods with Simulation*; Cambridge University Press: New York, NY, USA, 2009.
45. Newman, M.E.J. Communities, modules and large-scale structure in networks. *Nat. Phys.* **2012**, *8*, 25–31. [CrossRef]
46. Barabasi, A.L.; Albert, R. Emergence of scaling in random networks. *Science* **1999**, *286*, 509–512. [CrossRef] [PubMed]
47. Hexmoor, H. Argumentation for collaboration among internet of things. In Proceedings of the International Conference on Collaboration Technologies and Systems (CTS), Orlando, FL, USA, 31 October–4 November 2016. [CrossRef]
48. Rand, W.; Rust, R.T. Agent-based modeling in marketing: Guidelines for rigor. *Intern. J. Res. Mark.* **2011**, *28*, 181–193. [CrossRef]
49. Nobel Prize Committee; Richard, H. Thaler: Integrating Economics with Psychology; Nobel Prize in Economics Documents 2017-1. Available online: [https://ideas.repec.org/p/ris/nobelp/2017\\_001.html](https://ideas.repec.org/p/ris/nobelp/2017_001.html) (accessed on 21 March 2015).
50. Niroo Research Institute (NRI). Available online: <https://www.nri.ac.ir/evc> (accessed on 21 March 2015).
51. Nykvist, B.; Sprei, F.; Nilsson, M. Assessing the progress toward lower-priced long-range battery electric vehicles. *Energy Policy* **2019**, *124*, 144–155. [CrossRef]
52. Pollák, F.; Vodák, J.; Soviar, J.; Markovič, P.; Lentini, G.; Mazzeschi, V.; Luè, A. Promotion of Electric Mobility in the European Union—Overview of Project PROMETEUS from the Perspective of Cohesion through Synergistic Cooperation on the Example of the Catching-Up Region. *Sustainability* **2021**, *13*, 1545. [CrossRef]
53. Turoń, K.; Kubik, A.; Chen, F. When, What and How to Teach about Electric Mobility? An Innovative Teaching Concept for All Stages of Education. *Energies* **2021**, *14*, 6440. [CrossRef]
54. Eggers, F.; Eggers, F. Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. *Technol. Forecast. Soc. Chang.* **2011**, *78*, 51–62. [CrossRef]
55. Kotler, P. *Marketing Management: Analysis, Planning, Implementation and Control*, 9th ed.; Prentice Hall: Hoboken, NJ, USA, 1997.