

Article

A Study on the Interdependence in Sustainable Mobility Tools and Home Energy Equipment Choices

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Abstract: Energy consumption in transportation and households are the main two sections of energy consumption in Europe. To cope with the challenges raised by energy security, sustainability, and pollution, great efforts have been made to encourage the transition from fossil fuel vehicles to electric vehicles and car sharing. In terms of households, home renewable energy equipment such as heat pumps and solar panels are promising solutions. To accelerate the diffusion of these promising and environmentally friendly technologies, an abundance of studies has investigated the factors that impact the adoption of them. Most of the existing literature considered the choice behavior of vehicle types and choice behavior of energy equipment to be exogenous to other. Charging electric vehicles at home will lead to an increase in home energy costs. It is important to understand to what extent a household's decision to purchase new mobility tools or energy equipment is affected by the other. This paper, therefore, attempts to investigate the correlation between the choice of home energy equipment and the choice of new mobility tools. An inverted sequence stated preference experiment was designed and conducted in the Netherlands to examine the interdependence of mobility tools choice and home energy equipment choice. Two logit models were presented to investigate how the choice of mobility tools and energy equipment impact each other. Results indicate that the promoting effect between electric vehicles and solar panels is bidirectional, while the promoting effect between electric vehicles and heat pumps is unidirectional.

Keywords: electric vehicle; mobility tools; home energy equipment; interdependency choice behavior



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1. Introduction

Energy consumption in transportation and household are the main two sections of energy consumption in Europe. The transport sector accounted for 31% of total final energy consumption and the households sector accounts for about one-quarter [1]. To cope with the challenges raised by energy security, sustainability, and pollution, a series of measures have been taken on transportation sector energy consumption and home sector energy consumption. In terms of transportation, the electric vehicle has been expected to be one of the solutions to increase energy efficiency and reduce carbon emissions [2]. Great efforts have been made to encourage the transition from fossil fuel vehicles to electric vehicles. In addition to the adoption of new energy cars, reducing car ownership at the individual level is another solution. Car sharing has been promoted to reduce car ownership and increase energy efficiency [3,4]. In terms of household, home renewable energy equipment is one promising solution. The solar panel has been one of the most attractive solutions since it converts solar energy into electrical energy. The market share of rooftop solar panels has had quick and stable growth in past decades [5,6]. The application of heat pumps is another solution to meet the challenge of increasing power demand.

To accelerate the diffusion of these promising and environmentally friendly technologies, an abundance of studies has investigated the factors that impact the adoption of them. In the aspect of new mobility tools, households' socio-demographics, attributes of electric

vehicle and car sharing, policies, and psychological factors have been found to have an impact on the acceptance of them [7,8]. In terms of home energy equipment, similar to the new mobility tools, factors influencing consumer intentions to invest in solar panels and heat pumps can be mainly categorized into attributes of energy equipment and households' socio-demographics [9,10]. Most of the existing literature considered the choice behavior of new mobility tools and choice behavior of energy equipment to be exogenous to other. The decisions on them are independent of other decisions. There are growing interests in the interdependence between transportation behavior and energy behavior in the past decade. For instance, several studies found energy consumption behavior and travel behavior are correlated and both affected by changes in energy price [11]. Although these studies investigated the relationship between energy consumption and travel habit from behavioral perspectives, there has been less attention given to identifying whether the choice in mobility tools purchasing and choice in energy equipment affect each other. With the application of new mobility tools, charging for electric vehicles at home will lead to an increase in home energy costs. The increase in energy cost can be coped with the application of home energy equipment. Consequently, the use of electric vehicles may prompt to households install home energy equipment. In turn, households with residential solar panels have more motivation to purchase an electric vehicle to make full use of the generated electricity. The decision on mobility tools and the home energy equipment may be interdependent. Although this assumption is reasonable, it is difficult to be used as the foundation for current behavioral research or applied policy analysis without quantitative analysis. It is important to understand to what extent a household's decision to purchase new mobility tools or energy equipment is affected by the other.

Therefore, the objective of this research is to investigate the correlation between the choice of home energy equipment and the choice of new mobility tools. A novel approach of stated choice experiment which invert the sequence of choice was developed. Though the inverted sequence stated preference experiment, this study offers an approach to analyze the interdependent choice or joint choice. Using the stated preference data, this paper examines the interdependence of mobility tools choice and home energy equipment choice. Two mixed logit models were presented to investigate how the choice of mobility tools and energy equipment impact each other.

The paper begins with a review of existing knowledge on households' decisions on new mobility tools and home energy equipment. We then describe the survey and the collected data. Section 4 presents two logit models used to estimate the relationship between the choice of mobility tools and the choice of energy equipment. The results are discussed before the paper is completed with a discussion of the implications.

2. Literature Review

We review existing studies on the choice of emerging mobility tools and home energy equipment. In addition, previous studies about the relationship between households' decisions on energy and transportation are also discussed.

2.1. Choice of Emerging Mobility Tools and Home Energy Equipment

The literature on consumers' preference for electric vehicles is extremely rich in the past decades. The vast majority of the literature focused on the impacts of factors on the acceptance of electric vehicles. These factors can be categorized into cost-related factors [12,13], technical performance-related factors, consumer-related factors, and context-related factors. Cost-related factors include the purchase price, maintenance cost, and operation cost. Hoen and Koetse [13] conducted a stated choice experiment on alternative fuel vehicles including hybrid vehicles, plug-in hybrid vehicles, fuel-cell vehicles, and electric flexifuel vehicles. A mixed logit model was estimated. The results show that cost-related factors including purchase price, operation costs, and maintenance costs have negative effects on the preference for battery electric vehicles.

In addition to the cost-related variables, battery performance is another factor that has been widely investigated. The influence of driving range and charging speed has been discussed in previous studies [14]. Most of the previous studies have found driving anxiety is one of the main obstacles to purchasing an electric vehicle. Eppstein et al. [15] used an agent-based model to examine the sensitivity of factors including gasoline prices, battery range, etc. The result shows the willingness to pay added by longer-range batteries grows faster than linearly. Moreover, Sierzechula [16] collected data related to EV market share, financial incentives, urban density, education level, environmentalism indicator, and charging infrastructure from 30 countries. They estimated a logistic regression model. The results show people's intention to purchase an electric vehicle increase with the increasing charging convenience.

Regarding consumer-related attributes, the majority of previous study has investigated the influence of socio-demographics [17–19]. Age, education level, and income have been discussed. Hackbarth and Madlener [20] conducted a web-based discrete choice experiment related to alternative fuel vehicles. Results of a mixed logit model show young and well-educated males are more likely to purchase an electric vehicle. In addition to the socio-demographics, the living environment and personality of consumers were also found to have impacts on the preference for electric vehicles. Plotz et al. [21] conducted a statistical analysis of the socio-demographics and personalities of early BEV adopters in Germany. The study found that people with technical professions have a higher probability to purchase an electric vehicle.

The context-related factors mean the policy environment and service level of the charging infrastructure. The impact of policy incentives such as free parking or tax refund has been investigated in existing studies [22–24]. Most of these studies found the policies have positive effects on the acceptance of electric vehicles; however, some research did not find significant effects of these policies [25,26].

As for car sharing, the saving obtained from using car sharing instead of owning a car has a significant positive influence on the choice of car sharing. In addition, the impact of latent attitudes has also been analyzed. Kim et al. [17] collected data about respondents' personalities and conducted a stated choice experiment. They analyzed the effects of latent attitudes on car sharing using a hybrid choice model. Environment awareness and privacy-seeking were considered to impact the diffusion of car sharing.

The installation intentions of energy equipment are impacted by three types of factors including attributes of energy equipment, policies, and socio-demographics [27–29]. The cost and benefits of the energy equipment are the primary considerations in the choice of energy equipment [30,31]. Simpson and Clifton [32] interviewed householders who purchased a solar system and asked about factors that influenced their decision-making process. Results show that the incentives increase the affordability of solar panels and have positive effects on the preference for solar panels. In addition, the payback period of the investment in solar panels has also been discussed. Allen et al. [33] summarized and analyzed the market situation and policies of micro-generation in the UK and found the preference increase if a household can reclaim the cost of solar panels in time. Regarding the heat pump, costs were also found to have the highest negative effect on the acceptance of energy equipment. As for the impact of socio-demographics, the impact of income, age, gender, and education level on the attitude on energy equipment has been discussed [34,35]. Scarpa and Willis [30] conducted a stated preference choice experiment to analyze households' willingness to pay for renewable energy equipment in the UK. They found people who were influenced by social networks were more likely to invest in energy equipment.

2.2. The Relationship between Mobility Tools and Energy Equipment

The literature on the relationship between electric mobility tools and energy focus on the impact of electric vehicle charging on the energy demand and energy system. Putrus et al. [36] and Muratori [37] have estimated the influence of the application of

electric vehicles on the power grid. The results show electric vehicle charging may lead to dramatically increase in the residential electricity demand.

Some studies [38,39] proposed charging strategies in a smart grid including electric vehicles and renewable energy equipment. Saber and Venayagamoorthy [40] proposed an optimization model to reduce emissions from the electricity industry and the transportation industry. They analyzed the cost of electric vehicle charging in a smart energy system and found the combination of electric vehicles and energy equipment improves the efficiency of the energy system. Bedir et al. [41] simulated and evaluated the interaction between the grid, PHEV charging, photovoltaic power production, and residential load. They found a smart energy management system including solar panels, energy storage, residential load, and electric vehicles can save 40% of household energy expenditure.

Few studies analyze the relationship from the perspective of households' investment decisions. Coffman et al. [42] conduct a case study in Hawaii and used a scenario-planning approach for future fuel and electricity prices. They found households who are interested in the time-of-use rates for electric vehicle charging are more likely to install solar panels at home.

Although the choice of emerging mobility tools and choice of home energy equipment have been discussed by the abundant literature. However, studies on the relationship between electric vehicles and energy equipment focus on the efficiency of the combination. How the efficiency of the combination effect consumers' decisions on investment in mobility tools and energy equipment is rarely discussed. Thus, for the purpose of our research, we conduct a stated choice experiment and try to provide evidence of the mutual effect between the choice of mobility tools and home energy equipment.

3. Data Collection

3.1. Questionnaire Design

To investigate the comprehensive decision on mobility tools and home energy equipment, an online survey was conducted. The survey questionnaire includes questions about respondents' socio-demographics, characteristics of mobility, and details of the house they live in. In addition, an inverted sequence stated preference experiment about the choice of mobility tools and home energy equipment was conducted to measure the interdependence between them. The inverted sequence stated preference experiment is based on a context-dependent stated choice experiment which has been used in several existing studies [43–45]. In a context-dependent stated choice experiment, participants are asked to select an alternative while assuming a certain context. Respondents were asked about their priority in investment between mobility tools and energy equipment if they have the budget. After that, they were provided the hypothetical choice scenarios of mobility tools and home energy equipment. For people who prefer mobility tools, they were invited to make the choice of mobility tools first, then they were asked to make a choice of home energy equipment considering their decision on mobility tools. For people who prefer to invest in home energy equipment, they were asked to make the choice of energy equipment first and then make the choice of mobility tools considering the chosen mobility tools. For people who have equal priority on mobility tools and home energy equipment, they were given 4 choice scenarios with the order of mobility tools after energy equipment, and 4 choice scenarios in the opposite order. The details of each decision are presented below.

The stated choice question for mobility tools and choice question for energy equipment were constructed separately. Four alternatives were included in the choice of mobility tools: Electric vehicle, conventional vehicle, car sharing, and "none" option. A set of attributes and levels were used to describe each type of mobility tool. The levels for each alternative varied across the hypothetical choice scenarios.

3.2. Mobility Tools Choice

Attributes for each alternative were selected from aspects of total expenditures, incentive policies, and conveniences since these factors have been verified to have a significant

impact on the acceptance of mobility tools in previous studies [12–15]. We settled on the purchase price, maintenance cost, operating cost, driving range, charging speed, travel time to the charging station, and tax refund policy as the main attributes of electric vehicles. The price of vehicles is always one of the major factors. In order to improve the reality of the hypothetical vehicle choices and to reduce task complexity, the price of electric vehicles was set based on the price of the corresponding conventional vehicle. The purchase price of the electric vehicle was set to 10%, 20%, or 30% higher than the price of the corresponding conventional vehicle according to the current market situation [14]. The maintenance cost and operation costs are also key indicators of a new type of mobility tool. The operation cost of electric vehicles was set as 0.04 EUR/km and 0.08 km/km. The driving range was taken as representative of battery performance. Cirillo et al. [46] used the driving range of electric vehicles from 60 to 110 miles. Here, considering the development of battery technology and the market situation in the Netherlands, the driving range of electric vehicles was set to vary from 150 km to 450 km. As for the indicators of charging speed, fast charging time for 100 km was set as 5 min, 10 min, and 15 min, while the slow charging speed was set as 1.5 h per 100 km and 3 h per 100 km. Travel time to the nearest charging station was selected as the indicator for charging convenience, which was varied from 5 min to 15 min.

We settled on the purchase price, maintenance cost, and operation cost to describe the conventional car. Three levels were defined for the price of conventional cars: EUR 15,000, EUR 30,000, and EUR 45,000. The maintenance cost of a conventional car varied from EUR 100 per month to EUR 200 per month. Two levels were defined for the operation cost of a conventional car: 0.1 EUR per km and 0.15 EUR per km.

As for car sharing, the hourly rate is the main cost of car sharing. The levels of hourly rate were set to EUR 3 per hour and EUR 6 per hour according to most of the car-sharing companies. The probability of car availability, which is an important indicator of the reliability of car-sharing services, was set to vary from 60% to 100%. The access time to the nearest pick-up point had 3 levels, ranging from 5 min to 15 min. Attributes of mobility tools and their levels are shown in Table 1.

Table 1. Selected attributes and attribute levels of mobility tools.

	Attributes	Attribute Levels
Conventional vehicle	Purchase price (EUR)	15,000; 30,000; 45,000
	Maintenance costs (EUR/month)	100; 200
	Operating costs (EUR/km)	0.1; 0.15
Electric vehicle	Purchase price (EUR)	10%; 20%; 30% (higher than CV)
	Maintenance costs (EUR)	100; 200
	Operating costs (EUR/km)	0.04; 0.08
	Tax refund	5%; 10%; 15%
	Driving range (km)	150; 300; 450
	Average travel time to charging station (min)	5; 10; 15
	Fast charging time per 100 km (min)	5; 10; 15
Car sharing	Slow charging time per 100 km (h)	1.5; 3
	Maintenance costs (EUR/month)	0; 10; 20
	Operating costs (EUR/km)	0.2; 0.4
	Hourly rate (EUR/h)	3; 6
	Access time (min)	5; 10; 15
	Vehicle availability	60%; 80%; 100%

Based on the attributes and their levels, the full factorial design includes $2^7 \times 3^9$ different combinations. To increase the reliability of the choice design and avoid the multicollinearity problem, an orthogonal fractional design with 144 profiles was constructed to generate the choice set of mobility tools. Attributes of mobility tools were independently varied within and between options and presented equally. The design was then divided into 18 blocks. Each respondent was randomly provided with the choice profiles belonging

to one block. An example of a stated choices scenario of mobility tools is shown in Figure 1. Assume you are facing such a situation, you need to choose one from cars. Which option of car do you prefer?

	Buy an electric car	Buy a regular car	Join a car sharing	None
Purchase price	33000 euro	30000 euro	-	
Maintenance cost	200 euro/month	100 euro/month	20 euro/month	
Operating cost	0.04 euro/km	0.15euro/km	0.20 euro/km;	
Tax refund	10%	-	-	
Driving range	300 km	600 km	600 km	
Car availability	Always	Always	80%	
Charging time per 100km	fast charging :10 min; slow charging: 3 hour	-	-	
Travel time to charging station	5 min	-	-	
Access time	-	-	5 min	
Your choice	☐	☐	☐	☐

Figure 1. An example of the choice experiment of mobility tools.

3.3. Energy Equipment Choice

In the choice of energy equipment, respondents were asked to choose the option from the solar panel, heat pump, and “none” option. Solar panels and heat pumps were also described by a set of relevant attributes. The attributes purchase price, tax refund, payback period, and service life were selected to describe the energy equipment alternatives. Table 2 presented an overview of the attributes and their corresponding levels. The purchase price of solar panels varied from EUR 5000 to EUR 10,000 according to previous studies [47] and the market in the Netherlands. The price of heat pumps ranges between EUR 5000 and EUR 15,000. The payback period was defined here as the time users receive back all investments. The average acceptable payback period for PVs, according to Claudy et al. [34], is 9 years. As a result, three levels were defined for the payback periods of heat pumps and solar panels: 5 years, 10 years, and 15 years. The service life of energy equipment was set to 10 years, 20 years, and 25 years. The levels of tax refund were set according to the incentive policies in Europe, the percentage of the tax refund was set to no tax refund, 10%, and 20%. An orthogonal fractional factorial design of the 3^8 full factorial designs in 72 runs was created. The choice sets were divided into 9 blocks. The blocks were then assigned to the respondents randomly. Figure 2 shows an example of the choice tasks of energy equipment.

Table 2. Selected attributes and attribute levels of energy equipment.

	Attributes	Attribute Levels
Solar panels attributes	Purchase price (EUR)	5000, 7500, 10,000,
	Payback period (years)	5, 10, 15
	Tax refund	No tax refund, 15%, 30%
	Service life (years)	15, 20, 25
Heat pumps attributes	Purchase price (EUR)	5000, 10,000, 15,000,
	Payback period (years)	5, 10, 15
	Tax refund	No tax refund, 15%, 30%
	Service life (years)	15, 20, 25

Considering your household energy efficiency and the amount of money that you have available for spending after the choice of car, which option of home energy equipment do you prefer?

	Solar panel	Heat pump	None
Purchase price (including installation)	5,000 euro	10,000 euro	
Payback period of investment	10 years	5 years	
Tax refund	10%	20%	
Life span	15 years	20 years	
Your choice	☐	☐	☐

Figure 2. An example of the choice experiment of home renewable energy equipment.

3.4. Characteristics of Sample

The survey was conducted in June 2019 in the Netherlands. The URL of the web-based questionnaire was sent to a panel of a survey company in the Netherlands. The sample is picked randomly from the population of age 20 and older, since respondents younger than 20 are less likely to face a choice on home energy equipment in daily life. In the web-based questionnaire, if a respondent is younger than 21, the questionnaire will skip to the end.

In total, 974 respondents completed the questionnaire, of which 834 were valid after data cleaning. We have 6672 observations from 834 respondents since each respondent was asked to make choices for 8 choice situations. The sample size for logistic regression is normally larger than 10–20 EPV (events per variable) [48] or $100 + 50 \times \text{number of coefficients}$ [49]. The sample size is sufficient for analysis according to these studies.

Table 3 presents the sample distribution of the socio-demographic characteristics. It shows the percentages of males and females are almost equal. Regarding age, nearly half (44.8%) of the respondents are between 40–60, and the percentages for the group between 21–40 and for the group older than 60 years of age, respectively, are 37.8% and 17.3%. The frequency distribution of education suggests that more than half (56.4%) of the respondents receive a higher professional or university education. Regarding the household income of respondents, 39.3% of the respondents have an income lower than 3000 EUR/month. The majority of respondents have a medium-level household income between 3000 and 6000 per month. Nearly two-thirds (68.2%) of the sample has a paid job.

Table 3. Distribution of sample socio-demographic characteristics.

Characteristics	Levels	Percentage (%)
Gender	Male	49.3
	Female	50.7
Age	21–40	37.8
	41–60	44.8
	60+	17.3
Education	Secondary school or Lower	17.5
	College education	56.4
	Higher than college education	26.1
Income	Lower than 3000 EUR/month	39.3
	3000–6000 EUR/month	57.0
	Higher than 6000 EUR/month	3.7
Work	No paid work	31.8
	Paid work	68.2

4. Methodology

This study attempts to investigate the mutual effect between a choice of mobility tools and energy equipment. Therefore, the model for the impact of energy equipment on the mobility tools and for the impact of mobility tools on the energy equipment are estimated

separately. The logit model is one of the most common methods to investigate travel behavior and deal with the stated choice data [50,51]. Two logit models are estimated.

Model 1 identifies the impact of energy equipment on the choice of energy equipment. For the mobility tools choice situation t , the utility of alternative j for individual i is assumed to be stochastic, including a deterministic utility V_{ijt} and a random error term ε_{ijt} , the utility function can be expressed as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (1)$$

The deterministic utility is a linear function of observed variables including socio-demographics, the attributes of mobility tools, and context variables. In Model 1, respondents make decisions on mobility tools considering their choice of energy equipment; therefore, the choice of energy equipment was incorporated as the context variables. The utility function of mobility tools U_{ijt} can be written as:

$$U_{ijt} = \beta_{j0} + \sum_{k=1}^K \beta_k x_{ijtk} + \varepsilon_{ijt} \quad (2)$$

where x_{ijtk} is the k th explanatory variable related to attributes of the mobility tools, the choice of energy equipment, and the socio-demographics of individual i . β_k is the parameter for attribute k . β_{j0} is the alternative specified constant of alternative j . ε_{ijt} is a random error term that follows the IID Gumbel distribution. Respondents are assumed to choose the alternative that maximizes their utility.

The choice probabilities in the logit form can be written as:

$$p_{it}(j|\beta_{j0}, \beta_k) = \frac{\exp(\beta_{j0} + \sum_{k=1}^K \beta_k x_{ijtk})}{\sum_{j=1}^J \exp(\beta_{j0} + \sum_{k=1}^K \beta_k x_{ijtk})} \quad (3)$$

Model 2 investigates the choice of mobility tools on the choice of energy equipment. Like Model 1, the x_{ijtk} in Model 2 is the k th explanatory variable related to attributes of the energy equipment, the choice of mobility tools, and the socio-demographics of individual i .

Electric vehicles and car sharing are relatively new types of transportation, the decision-making process may be impacted by taste differences such as environmental consciousness and lifestyle. Therefore, a considerable amount of unobserved preference heterogeneity exists in the choice of mobility tools. Solar panels and heat pumps face the same issue. The mixed logit can easily handle correlation and heteroskedasticity between alternatives and random heterogeneity in preferences. [52,53] To incorporate the heterogeneity and explain its effect, the mixed logit model was used. The taste parameters β_k and β_{j0} are assumed to follow a normal distribution. Therefore,

$$\beta_{ik} = \bar{\beta}_k + \sigma_k, \quad k = 0, 1, 2, \dots, K \quad (4)$$

where $\bar{\beta}_k$ denotes the mean of the random parameter of attribute k . σ_k is the standard deviation of the random parameter β_{ik} .

The probability of the mixed logit model is given by

$$P_{ijt} = \int_{\beta_{j0}} \int_{\beta_k} p_{it}(j|\beta_{j0}, \beta_k) f(\beta_k) f(\beta_{j0}) d\beta_k d\beta_{j0} \quad (5)$$

5. Results

The results of the choice of mobility tools and the choice of energy equipment are presented in Tables 4 and 5, respectively. The MNL model and mixed logit model were estimated and compared. There are many parameters in the model, it is unrealistic to consider the taste differences for all attributes. To reduce the complexity, only the parameters for the alternative specific constant were considered random parameters. The estimate based on 1000 Halton draws was reported after systematically checking the estimates from

100 draws to 2000 draws. Model 1 improves the adjusted Rho squared from 0.527 (MNL model) to 0.612 (mixed logit model). Model 2 improves the adjusted Rho squared from 0.441 (MNL model) to 0.587 (mixed logit model). Results in Tables 4 and 5 indicate that almost all coefficient signs are consistent with expectations. Additionally, the standard deviations of the random parameters in the mixed logit model are statistically significant, which suggests the heterogeneity among individuals.

Table 4. Estimation results of Model 1.

Alternatives	Explanatory Variables	Coef.		SE	p Value
Electric vehicle					
Constant	constant _electric vehicle	0.272	**	0.131	0.039
Purchase price	10% higher than conventional vehicle	0.112	***	0.038	0.003
	20% higher than conventional vehicle	0.066	*	0.037	0.076
	30% higher than conventional vehicle	−0.178			
Maintenance cost	100 EUR/month	0.154	***	0.027	0.000
	200 EUR/month	−0.154	***	0.027	0.000
Operation cost	0.04 EUR/km	0.104	***	0.027	0.000
	0.08 EUR/km	−0.104	***	0.027	0.000
Tax refund	5%	−0.009		0.038	0.810
	10%	−0.067	*	0.038	0.076
	15%	0.076			
Driving range	150 km	−0.120	***	0.038	0.002
	300 km	0.044		0.038	0.247
	450 km	0.076			
Slow charging speed	1.5 h/100 km	0.029		0.027	0.282
	3.0 h/100 km	−0.029		0.027	0.282
Fast charging speed	5 min	0.041		0.037	0.275
	10 min	−0.029		0.038	0.443
	15 min	0.012			
Time to charging station	5 min	0.029		0.038	0.446
	10 min	0.000		0.037	0.991
	15 min	−0.029			
Age	20–40	0.188	***	0.055	0.001
	40–60	−0.081		0.068	0.233
	60+	−0.107			
Gender	male	0.023	***	0.038	0.007
	female	−0.023		0.038	0.537
Job	full job	0.031		0.091	0.728
	no full job	0.031		0.091	0.728
Income	low	−0.471	***	0.103	0.000
	middle	−0.302	***	0.099	0.002
	high	0.773			
Energy equipment	Solar panel	0.655	***	0.066	0.000
	heat pump	0.483	***	0.076	0.000
	none	−2.026	***	0.110	0.000
Conventional vehicle					
Constant	constant _conventional vehicle	0.425	***	0.127	0.001
Purchase price	15,000 EUR	0.224	***	0.036	0.000
	30,000 EUR	−0.018	***	0.036	0.540
	45,000 EUR	−0.206			
Maintenance cost	100 EUR/month	0.152	***	0.026	0.000
	200 EUR/month	−0.152	***	0.026	0.000
Operation cost	0.10 EUR/km	0.066	**	0.026	0.010
	0.15 EUR/km	−0.066	**	0.026	0.010

Table 4. Cont.

Alternatives	Explanatory Variables	Coef.		SE	p Value
Age	20–40	0.039		0.054	0.474
	40–60	0.105		0.064	0.101
	60+	−0.143			
Gender	male	0.019		0.037	0.602
	female	−0.019		0.037	0.602
Job	full job	0.060		0.087	0.491
	no full job	−0.060		0.087	0.491
Income	low	−0.427	***	0.101	0.000
	middle	−0.335	***	0.097	0.001
	high	0.761			
Car ownership	no car	−1.044	***	0.081	0.000
	1 car	0.391	***	0.054	0.000
	2 or more	0.653			
Energy equipment	solar panel	0.389		0.161	0.534
	heat pump	0.192		0.173	0.447
	none	−1.258		0.178	0.626
Car sharing					
Constant	constant _car sharing	−1.202	***	0.184	0.000
Maintenance cost	Free	0.086		0.069	0.214
	10 EUR/month	−0.095		0.071	0.183
	20 EUR/month	0.009			
Operation cost	0.2 EUR/km	0.013		0.050	0.786
	0.4 EUR/km	−0.013		0.050	0.786
Hourly rate	3.0 EUR/h	0.015		0.050	0.766
	6.0 EUR/h	−0.015		0.050	0.766
Time to pick-up point	5 min	0.143	**	0.069	0.037
	10 min	−0.037		0.071	0.600
	15 min	−0.106			
Availability	60%	−0.085		0.072	0.233
	80%	−0.052		0.071	0.462
	100%	0.138			
Age	20–40	−0.100		0.086	0.247
	40–60	0.077		0.101	0.447
	60+	0.023			
Gender	male	−0.085		0.059	0.146
	female	0.085		0.059	0.146
Job	full job	−0.255	**	0.121	0.035
	no full job	0.255	**	0.121	0.035
Income	low	0.018		0.145	0.902
	middle	−0.432	***	0.142	0.002
	high	0.414			
Energy equipment	solar panel	0.489	***	0.102	0.000
	heat pump	0.496	***	0.117	0.000
	none	−1.610	***	0.176	0.000
Standard deviation	electric vehicle	0.497	***	0.050	0.000
	conventional vehicle	0.482	***	0.032	0.000
	car sharing	1.072	***	0.041	0.000

Note: “****”, “***”, “**” mean significance at 1%, 5%, and 10% levels, respectively.

Table 5. Estimation results of Model 2.

Explanatory Variables	Levels	Coef.		SE	p Value
Solar panel	Constant	0.000		0.085	0.998
	EUR 5000	0.297	***	0.037	0.000
	EUR 7500	−0.039		0.037	0.289
	EUR 10,000	−0.258			
Payback period	5 years	0.326	***	0.037	0.000
	10 years	−0.046		0.037	0.220
	15 years	−0.280			
Tax refund	no tax refund	−0.321	***	0.037	0.000
	15%	0.021		0.037	0.564
	30%	0.299			
	15 years	−0.151	***	0.037	0.000
Age	20 years	−0.064	*	0.037	0.084
	25 years	0.215			
	20–40	0.572	***	0.053	0.000
	40–60	−0.106	**	0.046	0.022
	60+	−0.467			
	male	0.047		0.036	0.192
	female	−0.047		0.036	0.192
	full job	−0.013		0.038	0.743
	no full job	0.013			
	low	0.237	***	0.074	0.001
	middle	−0.031		0.067	0.648
	high	−0.207			
	apartment	−0.315	***	0.049	0.000
	terraced house	−0.088	**	0.039	0.023
	detached house	0.404			
	rent	−0.222	***	0.040	0.000
Mobility tools	own	0.222	***	0.040	0.000
	electric vehicle	0.916	***	0.092	0.000
	conventional vehicle	−0.030		0.075	0.689
	car sharing	0.174		0.158	0.273
	none	−1.844	***	0.117	0.000
Heat pump	Constant	−0.660	***	0.099	0.000
Purchase price	EUR 5000	0.535	***	0.040	0.000
	EUR 10,000	−0.135	***	0.043	0.002
	EUR 15,000	−0.401			
Payback period	5 years	0.444	***	0.040	0.000
	10 years	−0.035		0.042	0.410
	15 years	−0.409			
Tax refund	no tax refund	−0.308	***	0.043	0.000
	15%	0.007		0.042	0.859
	30%	0.301			
Service life	15 years	−0.250	***	0.043	0.000
	20 years	0.051		0.042	0.216
	25 years	0.199			
Age	20–40	0.549	***	0.059	0.000
	40–60	−0.101	*	0.052	0.055
	60+	−0.448			
Gender	male	0.086	**	0.041	0.035
	female	−0.086	**	0.041	0.035
Job	full job	0.006		0.043	0.882
	no full job	−0.006		0.043	0.882
Income	low	0.148	*	0.084	0.077
	middle	0.051		0.076	0.504
	high	−0.199			

Table 5. Cont.

Explanatory Variables	Levels	Coef.		SE	p Value
House type	apartment	−0.137	**	0.056	0.014
	terraced house	0.034		0.044	0.437
	detached house	0.103			
House ownership	rent	−0.379	***	0.047	0.000
	own	0.379	***	0.047	0.000
Mobility tools	electric vehicle	0.961	***	0.103	0.000
	conventional vehicle	−0.185	**	0.090	0.041
	car sharing	0.618	***	0.168	0.000
	none	−2.200	***	0.170	0.000
Standard deviation	solar panel	0.185	***	0.049	0.000
	heat pump	0.401	***	0.073	0.000

Note: “***”, “**”, “*” mean significance at 1%, 5%, and 10% levels, respectively.

5.1. Choice of Mobility Tools

According to the results, the alternative specific constants of electric vehicles and conventional vehicles are positive, while the alternative specific constant of car sharing is negative. It suggests that respondents indicate owning a mobility tool rather than using a shared car.

Variables related to the cost of electric vehicles are statically significant. The purchase price is found to have a significant negative influence on the utility of the electric vehicles. The coefficient decreases near linear trend when the price relative to conventional vehicle increase from 10% higher to 30% higher. For the maintenance cost and operation cost of electric vehicles, in line with the previous studies, our results show maintenance cost and operation costs have a significant effect on the acceptance of electric vehicles. The tax refund policy incentivizes the acceptance of electric vehicles. The coefficient signs of the driving range at 300 km level and 450 km level are negative, suggesting people are more likely to purchase an electric vehicle when the driving range is longer than 300 km. The coefficients of driving range decrease sharply when the driving range is shorter than 300 km, imposing that an electric vehicle with a driving range near 150 km is unacceptable for users. In terms of the charging speed and convenience factors, the faster charging speed is positively related to the utility of charging speed. The coefficients for the fast charging speed are larger than the slow charging speed. It may suggest that people are more concerned about the fast charging speed than the slow charging speed. The shorter travel time to a charging station has a positive effect on the utility of electric vehicles.

For conventional vehicles, the purchase price has a negative effect on acceptance, which is in line with most previous studies. The coefficients of operation cost and maintenance cost at the lower level are positive, which suggests the higher the operation cost and maintenance cost, the lower the acceptance of conventional cars. For car sharing, the parameter for maintenance cost at the free level is found to have a significant and positive effect on the acceptance of car sharing. However, the difference between the coefficients at 10 EUR/month and 20 EUR/month levels is minimal, which might be explained by the fact that people do not mind being a member of a car-sharing program; however, the intention will be fast running out if it is not free. The operation cost and hourly rate have no significant effect on the utility of car sharing. However, the time to a pick-up point and availability has a significant impact. The utility of car sharing increases with decreasing time to a pick-up point. The availability of car sharing significantly increases the acceptance of car sharing, especially when the availability is 100%. The difference indicates that people are more sensitive to the service level and convenience of car sharing than the cost.

In terms of the socio-demographic characteristics, the results show age and gender has significant impacts on the acceptance of electric vehicles, while having no significant effect on the acceptance of conventional cars and car sharing. The results show that males between 20 and 40 years have a higher probability of purchasing an electric vehicle. People who have

a job are less likely to join a car-sharing program. As for incomes, people with high incomes prefer electric vehicles to conventional vehicles. Table 4 also lists the results of the standard deviation of the random parameters. The results show the standard deviation between electric vehicles and car sharing is statistically significant. It suggests that unobserved taste heterogeneity of the preference for electric vehicles and car sharing. The alternative specific constant of the different mobility tools did not capture the preference for electric vehicles and car sharing.

For the effects of the adoption of energy equipment on the acceptance of mobility tools, which is one of the main objectives of this study, the results also provide evidence. The positive signs of the solar panel show that people who have chosen the solar panel have a higher probability to choose car sharing and electric vehicles, especially the latter. For the choice of heat pump, it was also found to have a positive effect on the utility of electric vehicles and car sharing. However, the effect of choosing a heat pump on the preference for electric vehicles is almost the same as its effect on car sharing.

5.2. Choice of Energy Equipment

Table 5 lists the results of the choice of energy equipment. In terms of the attributes of solar panels and heat pumps, the coefficients of the price at a lower level are statistically significant and positive. The coefficients of price near linear decrease with increasing price. The payback period for 5 years is positive. The coefficients of the payback period for solar panel and heat pump decrease linearly increase when the payback period increase from 5 years to 15 years. The results reveal that 10 years is near the acceptable payback period for respondents. The tax refund representing incentives for investment in sustainable energy equipment has a statistically significant effect on the acceptance of solar panels and heat pumps. The coefficients of a tax refund at the 15% level and at the 30% level are both positive. The coefficient signs of the service life at 25 years for solar panels and heat pumps are both positive, indicating the service life also has notable positive effects on the acceptance of energy equipment.

As for the socio-demographic variables, the results show that people between 20–40 years prefer to purchase solar panels and heat pumps. Furthermore, the coefficient for gender has no significant effect on the acceptance of solar panels while it has a significant effect on the heat pump. Males are more likely to choose heat pumps than females. The working situation has no significant effect on the acceptance of energy equipment. As for attributes related to the house, negative effects are found for people who rent a house and people who live in an apartment. The results of the standard deviation show that the standard deviation of solar panels and heat pumps is statistically significant, implying that unobserved heterogeneity exists in the choice of energy equipment.

As for the effect of mobility tools, the results show purchasing an electric vehicle has a positive effect on the acceptance of solar panels and heat pumps. The purchase of a conventional car has a negative effect on the acceptance of solar panels and heat pumps, while car sharing has no significant effect. When people purchase an electric vehicle, the energy bills for the household may increase, results of this study show that they are inclined to purchase energy equipment to offset the increasing energy cost.

6. Conclusions

The vast literature on individuals' preference for new mobility tools including electric vehicles and car sharing mainly focuses on the influence of socio-demographics and attributes of mobility attributes. With the application of V2G and V2H technology, the electric vehicle, and house energy system are connected. Consequently, purchasing an electric vehicle may influence households' decisions on home energy equipment such as solar panels and heat pumps. On the flip side, installations of home energy equipment may increase interest in emerging mobility tools to improve the efficiency of energy use.

Therefore, it is necessary to investigate the mutual effect between the choice of mobility tools and energy equipment. Moreover, electric vehicle, car sharing, solar panels, and heat

pumps are relatively new products, and the taste heterogeneity across the population need to be examined. Although the impact of electric vehicle charging on the energy demand and energy system has been investigated, how the synergy between electric vehicles and energy equipment influences a household's purchasing intention has not been analyzed. Therefore, this study contributes to the existing literature by investigating the mutual effect between the choice of mobility tools and the choice of energy equipment from the perspective of the decision-making process. An empirical study was conducted using a sequential stated choice experiment. Results show that the choice of electric vehicles has a significant effect on the acceptance of solar panels and heat pumps. However, the installation of heat pumps has no significant effect on the acceptance of electric vehicles. In other words, the promoting effect between electric vehicles and solar panels is bidirectional, while the promoting effect between electric vehicles and heat pumps is unidirectional. The results of this study can provide guidance for the strategy for promoting and selling electric vehicles and sustainable energy equipment. Policymakers should take advantage of the influence of the synergy effect between mobility tools and energy equipment on their purchase intentions. The synergy between these two types of technologies can help to increase the penetration of each other. The growing electric vehicle market presents an opportunity for the diffusion of energy equipment. Policymakers should consider offering combined discounts or tax incentives for both mobility tools and energy equipment, as this may be more effective than focusing on just one of these technologies.

The current study still has several limitations. First, while this study took respondents' heterogeneity into account, it did not examine the sources of heterogeneities. The latent characteristic of respondents, like personality or lifestyle, may be the cause of heterogeneity. Future research could set indicators to evaluate these possible factors to examine the origins of heterogeneity. Second, this research only examined the mutual effect between mobility tools and energy equipment, it did not consider other energy technologies such as energy storage technologies, etc. Future research may focus on interactions among them that are more complicated. We would leave these considerations to our future work.

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