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The impact of learning and short-term experience on preferences for electric vehicles

C. Aravena [a], E. Denny [b,*]

[a] Department of Economics, Edinburgh Business School, Heriot-Watt University, Edinburgh, EH14 4AS, United Kingdom
[b] Department of Economics, Trinity College Dublin, Arts Building, Dublin 2, Ireland

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ABSTRACT

The transport sector is a key contributor of global greenhouse gas emissions and electric vehicles have become a focus in striving to achieve decarbonisation and efficiency in the sector. This study uses a stated preference methodology, specifically choice experiments, to investigate the attitudes and preferences of potential buyers for a number of technical, environmental and policy attributes of electric vehicles in Ireland. We specifically focus on whether learning through provision of information and a brief vehicle experience affects preferences and welfare measures. Previous studies have examined the role of lengthy electric vehicle demonstration trials, for example 3 month trials, on preferences. This paper addresses a gap in the literature by considering the role of much shorter scale experience (minutes rather than months) on attitudes which more closely represents the experience that a potential purchaser will have at the point of investment. Using random parameter models, our results show that people are willing to pay more for certain technical and environmental features of electric vehicles, however, policy measures such as preferential parking rates are seen to have a non-significant effect on utility of participants. The learning process increases the significance of the environmental component, and produces significantly higher willingness to pay for increased battery range and vehicle size.

1. Introduction

The transport sector is responsible for approximately 50% of oil consumption worldwide and the largest proportion of energy related CO_2 emissions [1]. Increasing electric vehicle (EV) uptake has been identified as a key strategy in supporting the decarbonisation and efficiency of the transport sector in many countries [2–7] while also contributing to security of supply by increasing fuel diversity in transport. However, sales of EVs have been slow with the primary reason cited as being the high capital cost when compared to conventional vehicles [5,8–10]. Previous research has shown that individuals are aware of some benefits associated with EVs and value their attributes. Nevertheless, final purchasing seems to be strongly affected by the high purchase cost of these vehicles compared to conventionally fuelled vehicles.

In this article we are interested in studying the effect of learning and experience on the stability of preferences for electric vehicles. We examine the importance of learning through provision of information and a brief experience with the good (EV) on preferences and welfare measures. We hypothesise if preferences are stable; the introduction of learning by information and experience should have no impact on attribute valuation. Other papers in the field have examined the impact of experience on electric vehicles attitudes, for example, through demonstration trials where participants experienced an EV for three months [11,12]. We explore the impact of shorter scale experience (minutes rather than months), on attitudes. We believe this is a vital contribution to the field, which has not previously been examined as it more closely represents the experience that a potential purchaser will have at the point of investment.

In this paper we use a discrete choice experiment to study preferences and attitudes of potential buyers of plug-in EVs for different types of EV attributes, before and after information and a brief experience with an EV, in Ireland. It builds on a recent paper by Mukherjee and Ryan [13] which considers the importance of awareness and attitudinal variables for early adopters of EVs in Ireland. Their work focuses on households who have already adopted an EV, whereas this paper examines preferences for potential future EV buyers. Our paper includes three elements; technical characteristics of plug-in EVs, environmental benefits and policy measures in order to investigate the trade-off between these types of attributes and the willingness to pay by potential buyers for each of them.

* Corresponding author.
E-mail address: dennye@tcd.ie (E. Denny).

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Abbreviations:

CO_2	Carbon Dioxide
g	grams
ESB	Electricity Supply Board,
EV	Electric Vehicle
ICE	Internal Combustion Engine
i.i.d.	independent and identically distributed
km	kilometre
kWh	kilowatt-hour
OOR	opt-out reminder
U_{ni}	Individual n's utility function for good i
WTP	Willingness to pay

The key research question examined in this paper is whether learning through provision of information and a brief vehicle experience affects preferences and welfare measures for EV attributes. A key contribution of this paper is that we explore the impact of a short scale experience (minutes rather than months), on attitudes. We believe this is an important contribution to the field, which has not previously been examined, and which more closely represents the actual experience a consumer might encounter in a car showroom when considering purchasing an electric vehicle (rather than a longer trial as has been investigated in other work). Using a discrete choice experiment estimated with a random parameter model, we find that participants are willing to pay a premium for larger electric vehicles with increased range and shorter battery charging times. We find that learning and short-term experience of an EV increases the significance of the environmental benefits associated with electric vehicles. However, we also find that learning and short-term experience of electric vehicles has only a small effect on preferences.

The structure of the remainder of the paper is as follows: the literature review and context is provided in Section 2; the methodology and the choice experiment design are provided in Section 3; the results and discussion are in Section 4 and 5 respectively; and the conclusion is provided in Section 6.

2. Literature review

There is a large and growing literature using stated preference methods to examine individuals' attitudes in the transport sector. For example [14–17], use stated preference approaches to evaluate the demand for electric vehicles and highlight the importance of large incentives to reduce the purchasing price. More recent papers have included policy attributes in addition to technical and financial attributes, for example, Bolduc et al. [18] use a stated preference approach to consider vehicle choice between conventional and alternatively fuelled vehicles including both vehicle characteristics as well as a policy measure (for example, access to the express lane) but find that the policy measures are the least important in terms of affecting the stated decision. Other papers also include policy features such as free-parking, bus lane access and tax incentives [9,19–21]. Findings indicate that reduced costs and purchase tax relief would encourage uptake but the parking and express lane attributes were found to be non-significant. Guerra & Daziano [22] also consider parking spaces in preferences for EVs using a stated choice experiment and examine if participants would be willing to pay for dedicated parking spaces with charging points. They find a $100 per month parking charge decreases the odds of purchasing an EV by approximately 65%.

Qian et al. [23], conduct an online choice experiment among consumers in China to study the trade-offs between vehicle characteristics, service attributes and governmental policies, where the latter includes the "vehicle-licensing regulation". They find that charging facilities in the home is the most important attribute and the free license plays an important role in policies to encourage EV adoption. Using a stated preference study on 2200 Californian households, Adler et al. [24], found that in addition to vehicle characteristics (such as fuel savings and purchase subsidies), policy measures such as free parking were a significant motivating factor in encouraging households to select the alternatively fuelled vehicle.

Rezvani et al. [25], presents a review of the advances in consumer EV adoption and concludes that it is important to study the perception of consumers about policies related to adoption of EVs as well as the connection between EVs and the environmental protection, a result supported by Mukherjee and Ryan [26] for Ireland. This paper presents a choice experiment for EVs which consider three types of attributes, technical, environmental, and policy attributes, in a single choice set for electric vehicles.

While the choice experiment with policy attributes is a contribution to the growing literature in this field, a key objective of the paper is to study whether learning through information and experience influences stated choices and marginal values in a choice experiment. To examine this issue we use an iterative rather than a split sample approach, using the same choice experiment after the provision of information and a brief experience of the good.

Previous research has showed that provision of information can overcome many anomalies in stated preference studies. For example, in the field of experimental economics learning has been shown to mitigate major theoretical preference anomalies such as the willingness to pay – willingness to accept differences and the endowment effect [27]. In double-bounded contingent valuation studies, the introduction of information about decision rules has also been shown to reduce the well-known anomaly of internal inconsistency between single and double bounded responses [28,29].

Previous research on learning and experience with electric vehicles has shown that preferences for EVs can change once the individual has hands-on experience with a vehicle. For example, Jensen et al. [11] run a field trial where 369 volunteers are provided with an electric vehicle for 3 months. They conduct a choice experiment with the volunteers prior to experiencing the vehicle and then again after the 3-month period has finished. They find that experience with the vehicle causes a major change in the preferences for driving range, top speed, fuel cost, battery life and charging in city centres and train stations.

Similarly, Franke and Krems [12] examine the factors that influence the preferences of 79 potential EV drivers following the opportunity to drive an EV for 3 months. Their study focusses on preferences about driving range and they find that experience of an EV results in a decrease in the importance of range preferences.

While both of these studies provide a fascinating insight into the benefits of trialling an EV on preferences, it is not practical to envisage a scenario where any potential EV buyer will have the opportunity to first trial a vehicle for three months. Thus, in this paper we examine preferences before and after information provision and a brief experience of an EV (minutes rather than months), which is more in line with the actual experience a consumer might encounter when considering purchasing an electric vehicle at a car showroom. This is extremely important from a policy perspective as the costs of providing a lengthy EV trial for any potential purchaser is prohibitively expensive as a policy measure thus, it is critical to examine the potential impact of information provision and initial vehicle impressions as a more realistic approach to encouraging uptake. We believe this focus on simulating the sort of information which might be provided at the point of making the investment decision is more realistic and fills an important gap in the existing literature.

It should be noted that this paper assumes that electric vehicles will offer environmental savings, as is the case in Ireland. When comparing the environmental impacts of EVs versus conventional vehicles, it is useful to consider the entire production chain. The production of lithium batteries has an important role in the emissions associated with the production of EVs when compared to conventional diesel and petrol vehicles. According to Messagie [30], the CO_2 emissions from manufacturing, maintaining, and recycling the vehicle, the motor, the battery and the electronics are almost twice as high for EVs as for equivalent diesel vehicles. However, these higher production emissions have the potential to be mitigated by lower operating emissions. The operating emissions will vary from country to country and will depend on the nature of the power system generating the electricity and the time of day when the electric vehicle is charged i.e. the marginal power plant on the system when the EVs are being charged [6,31].

The emission reduction benefits of EVs will be at their lowest in countries where the marginal power plants produce high emissions. For example, in a country such as Poland, where almost 100% of the marginal power plants are coal fired, or in Germany where the marginal unit is often lignite, the emission benefits of EVs will be lower (or even negligible/negative) compared to a power system where the marginal power plants produce low or zero emission. In Norway or Iceland where the marginal plants are almost 100% zero-emissions, the emissions benefits of EVs will be maximised [31–33].

Ireland, as the case study system, is generally considered a favourable location for electric vehicles given the relatively short driving distances between key cities and the characteristics of the Irish power system. In Ireland, natural gas-fired combined cycle and open cycle gas turbines power plants are typically the marginal units in the wholesale electricity market and in 2018, the CO_2 intensity of the marginal gas fired plants in Ireland was 366gCO_2/kWh [34,35]. The most popular electric vehicle in Ireland is the Nissan Leaf, with a fuel economy of 164 Wh/km [36]. Assuming this car was charged with the marginal gas unit it would equate to 60 g/CO_2 per km which is 51% lower than the average CO_2 emissions of new passenger vehicles sold in the EU in 2019 [37]. Thus, EVs are considered a key component of achieving reduced total CO_2 emissions in Ireland.

It should also be considered that electricity systems across Europe are transitioning to zero carbon by 2050 which will shift older, high emissions units out of the merit order and will improve the emissions benefits of EVs across all countries. Also, the increasing use of digitised smart meters indicating time of use pricing and real-time CO_2 emissions will help to motivate EV users to charge their vehicles at low price/low CO_2 times.

3. Materials and methods

This study uses a stated preference method, specifically Choice Experiments [38,39] to study the stability of preferences for electric vehicle attributes with respect to learning by information and experience. The methodology in choice experiments is derived from the Lancastrian approach which considers that an individual n obtains utility from the attributes or characteristics of a good, rather than directly from the good itself [40]. From random utility theory [41], it is assumed that an agent's linear utility function (U_{ni}) is comprised of two parts, the first of which (V_{ni}) is observable by the analyst, while the second, (ε_{ni}), is unobservable and is assumed to exhibit stochastic behaviour according to an i.i.d. process as follows:

$$U_{ni} = V_{ni} + \varepsilon_{ni}. \tag{1}$$

The deterministic part of the utility function (Vni) is a linear function of the parameters corresponding to each attribute. Therefore, Vni can be expressed as

$$V_{ni} = \beta_n^{'} X_{ni} \tag{2}$$

where β_n is the vector of parameters corresponding to the attributes for individual n and X_{ni} is the vector representing the attributes for individual n for alternative i.

During a choice experiment, participants are given repeated choice tasks with two or more options, described by attributes and levels, from which they select their preferred option. It is assumed that individuals will select the option that gives them the highest utility, and as such, their preferences are revealed. In this paper, our choice sets consisted of three options (known as alternatives): two generic alternatives which involve an electric vehicle and a fixed status-quo alternative, which is a conventionally fuelled vehicle. Participants were requested to select their preferred alternative among the three vehicle options. Table 1 presents an example of a choice set used.

Given the stochastic component of the utility function, we rely on probabilities for the estimation of the empirical model. Therefore, the generic logit probability of a sequence of T individual choices is given by the expression:

$$P_{ni} = \int \left(\prod_{t=1}^{T} \frac{\exp\left(\beta_{ni}^{'} X_{ni}\right)}{\sum_{j=1}^{J} \exp\left(\beta_{nj}^{'} X_{nj}\right)} \right) f(\beta) d\beta \, \forall \, i \neq j \tag{3}$$

where i and j are alternatives presented in the choice set.

The attributes and levels used in the design of our choice experiment were selected from a careful revision of the existing literature using similar techniques (e.g. Refs. [9,11,12,14,15and16]) and by using a series of focus group discussions with the participation of representatives from a large electricity utility company in Ireland (ESB Ireland), representative drivers (selected from the general public), and expert transport economists and engineers. This process facilitated the selection of the relevant attributes and levels for the choice sets in this study. It was not possible to customise the choice sets for each individual in our study given that it was paper based, for example tailoring the conventional vehicle attributes to be consistent with a participant's existing vehicle, but this is an area of consideration for future work.

The attributes used to describe the electric vehicles in our choice experiment are as follows: (1) driving range on full battery, (2) battery charging time, (3) battery life, (4) reduction in CO_2 emissions, (5) possibility of plug-in hybrid back-up, (6) size, (7) top speed, (8) reduction in parking fee (also called supporting on-street parking policy) and (10) purchase price. The value of these attributes was based on a number of pre-defined levels. A description of the attributes, and their levels, used in the choice experiment is presented in Table 2. Most of the attributes are numerical and are coded as such in the econometric model i.e. with the corresponding level (number) of the respective attribute. For example, for the attribute "driving range on full battery" there are three levels: 100, 200 and 400 km; these are coded as 100, 200 and 400 respectively in the random parameter model. The only variable that is non-numerical is the possibility of plug-in hybrid back-up, which is

Table 1
Example of a choice set.

	Electric Vehicle 1	Electric Vehicle 2	Conventional Fuelled Vehicle
Driving range on full battery	200 km	400 km	300 km
Battery charging time	20 min	8 hours	Electric battery not needed but 15 min to fill the tank at a petrol station.
Battery Life	12 years	5 years	Electric battery not needed
Reduction in CO_2 emissions	30%	50%	0%
Possibility of plug-in hybrid back-up	Yes	No	Not applicable
Size (Number of seats including the driver's seat)	2 seats	4 seats	5 seats
Top Speed	150 km/h	200 km/h	200 km/h
Supporting on street parking policy	30% off the normal price	50% off the normal price	Full parking charge
Purchase Cost	€20,000	€25,000	€15,000
Tick your choice			

Source: Authors' design

Table 2
Description of attribute and levels used in the choice experiment design.

Attribute	Description	Levels	Attribute	Description	Levels
Driving range on full battery	Kilometers that can be driven in the EV using a full charge tank.	• 100 km • 200 km • 400 km	Size	Number of passenger that can be seated in the car including the driver.	• 2 seats • 4 seats • 5 seats
Battery charging time	Time needed to fully charge the battery of the electric vehicle.	• 20 min • 2 h • 6 h • 8 h	Top speed	Maximum speed the vehicle can reach.	• 120 km/h • 150 km/h • 200 km/h
Battery life	Years that battery will last providing a good performance before being replaced, considering a yearly use of 15,000 km.	• 5 years • 8 years • 12 years	Supporting on street parking policy	Reduction in parking fees in public spaces	• 30% off normal price • 50% off normal price • Free Parking
Reduction in CO_2 emissions	Reduction in CO_2 emissions assuming the new electricity is generated by renewable sources	• 30% • 50% • 100%	Purchase Cost (after subsidy)	Total purchase price to buy the car, including the incentive or subsidy obtained from the Government.	• € 10,000 • € 15,000 • € 20,000 • € 25,000
Possibility of plug-in hybrid back up	Possibility of including a facility in the EV to allow it to be fuelled by conventional fuel.	• No • Yes			

treated as a dummy variable and is assigned the value of 1 when the level was “yes” and 0 otherwise.

The scenario description presented to individuals stated that the vehicles presented were identical in all respects apart from across the attributes mentioned (and listed in Table 2). No variability is assumed in the levels of the conventional vehicle attributes, these were fixed for all respondents (as per column 4 in Table 1) and are indicative of the average status-quo. In addition, the instructions included a cheap talk script in an effort to mitigate against hypothetical bias.[1]

The choice sets shown to participants were built based on a full factorial design from which 32 choice sets were created using cyclical design [42]. Choice sets were blocked into eight groups and each respondent was assigned a total of four choice sets. Overall, sixteen survey arrangements (8 blocks) were generated with the order of choice sets presented being inverted to control for order effect. Surveys were randomly allocated among participants. Surveys were completed by participants at the same time in a single location using pen and paper.

Respondents were given the survey and asked to complete the first section, which consisted of general attitudinal questions and some background and demographic questions. They were then asked to pause while one of the researchers presented some brief information (about 5 min) about the scenario and the attributes and levels. This scenario included a general description of the electric vehicle characteristics which would be shown in the choice sets along with information about the environmental benefits and challenges, and a brief comparison of electric vehicles and conventionally fuelled vehicles.

In addition, the short presentation provided an overview of the current EV support policies in Ireland with information on national EV targets. The benefit of presenting the choice experiment like this instead of a typical written scenario, which is read either by the interviewer or the respondent, is that all respondents get exactly the same information in exactly the same way, avoiding bias such as interviewer bias. This approach also represents an innovation to the typical method of presenting choice experiments.

After the presentation of the scenario, an example of the choice set was shown to participants and they were introduced to the next part of the survey, which was the choice experiment task. Finally, respondents were asked to complete the final section of the questionnaire consisting of further background questions.

To examine the impact of learning and experience we introduced a treatment to our study. This was conducted 14 days after the first choice experiment as described above. A representative from the Electricity Supply Board (ESB) - the main Irish electricity company responsible for the EVs’ program in Ireland – supplied an electric vehicle (Nissan Leaf) for demonstration and observation by the participants. Participants had the opportunity to sit in the car, turn it on and be a passenger for a short ride (the distance travelled was constrained due to space and time limitations).[2]

After the physical demonstration session with the vehicle, participants were taken to the same location in which they completed the first choice experiment. They attended a half-hour seminar, given by the ESB representative, in which he explained the different aspects of electric vehicles and the history and potential of their deployment in Ireland. In order to avoid information bias we made sure the presentation was objective and did not highlight or prioritize any attribute over the others. The presentation from ESB was balanced and presented both the potential economic and environmental benefits but also highlighted the challenges of EVs including a limited charging network in Ireland, long recharging times, limited top speeds, limited battery life and other potential downsides like the lack of noise which may increase accidents with pedestrians and cyclists. It is important to note that the presentation was objective (as our aim was to avoid information bias). The ESB representative was given a limited time (20 min) for their presentation and we communicated with them in advance to ensure the presentation was balanced in terms of benefits and drawbacks of EVs. This was followed by a short question and answer discussion session. The purpose of the discussion session was to give participants the opportunity to seek further information on electric vehicles similar to the type of questions they might ask at the point of sale or to peers who own an EV. After this presentation and discussion session respondents were asked to again

[1] Following Ladenburg et al. (2014) we also used an Opt-Out Reminder (OOR), which consists in adding a short cheap talk script before the presentation of each choice set in order to avoid hypothetical bias.

[2] We should note that the term “experience” in this paper is thus limited, as participants were able to see the car and get into it but were only taken on a journey of a few 100 m. This was due to the limited space of the demonstration site (university campus) and the time constraints of participants and demonstrators.

answer the choice experiment. We used exactly the same choice experiment designed in the previous treatment and questionnaires were again distributed randomly.[3]

Both choice experiments were conducted in a large lecture theatre in Trinity College Dublin with students from 23 different degree programmes across a range of disciplines (from social sciences to business to computer science). This facilitated a large participation level and minimised attrition between survey rounds and between EV demonstration and the completion of the survey. Ethical approval was provided for a paper-based survey rather than online to ensure no students were excluded from participation due to lack of smartphone/laptop. While it is recognised that the student population is not representative of the general population in terms of income, age, education and other variables, it is hypothesised that students are potential future consumers of electric vehicles and may provide some insights regarding perceptions of EVs. It is also important to note that the focus of this paper is on the methodology employed and the behavioural aspect (the focus on preference stability) rather than on policy recommendations and the authors advise caution in interpreting the results with respect to future policy design and recommend a more representative sample be utilised before the results can be generalised.

Following the standard approach for stated preference analysis (for example, Louviere et al. [38] and Cirillo et al. [10]) we used a random parameter multinomial logit model to estimate and analyse our results [43], where the error term is assumed to be i.i.d. type I extreme value. This model allows us to consider unobserved heterogeneity associated with the individuals' responses and the utility parameters vary between them instead of being fixed. The integral for the choice experiment is at the individual level. We calculate the marginal Willingness to Pay (WTP) for each attribute by using the parameter estimates and assuming a linear utility function. A linear specification is assumed for the utility function in line with the standard approach in the literature (for examples see Refs. [9,14,44,45] among others). The marginal WTP is given by dividing the parameters of the non-monetary attributes between the parameter of the cost attribute (purchase price). In a similar approach to Ref. [11] we assume that observations are independent across time.

4. Results and discussion

We received a total of 215 responses to the choice experiments in our first treatment from which 192 were useable.[4] For our second treatment we received 132 responses from which we could use 123.[5] We made sure that all responses obtained in our second treatment corresponded to individuals that were present in the first round (the treatment without learning and experience). A summary of the sample characteristics is provided in Table A1in Appendix A. As can be seen from Table A1, since this is a sample of students, there is very little variation in terms of key demographics e.g. age and education. The overall share of EV choices in the first round was 89.5% and in the second round was 90.5%.

We used the software NLogit 6 to estimate a random parameter logit model which allows us to account for non-observable heterogeneity among individuals. We estimated several models, first considering all parameters as random and then reducing the model to include as random those that were significant. We consider the ASC for each treatment as random and selected the final model based on the one that presented the best fit (see Table 3). Battery life and speed were found to be non-significant and are therefore treated as non-random. We assume a normal distribution for the random parameters. We find that our

Table 3
Estimation results – random parameters logit model.

ATTRIBUTES	Choices without learning and experience	Choices with learning and experience
	Random Parameters	Random Parameters
Driving range (km)	0.0039***	0.0056***
	(0.001)	(0.001)
Battery charging time (hours)	−0.120**	−0.086**
	(0.051)	(0.037)
Reduction in CO_2 emissions (%)	0.004	0.009***
	(0.005)	(0.003)
Plug-in hybrid back-up (Yes/No)	−0.301	0.068
	(0.243)	(0.173)
Size (# of seats)	1.20***	0.92***
	(0.280)	(0.146)
On street parking policy (yes/no)	−0.005	0.002
	(0.007)	(0.005)
Purchase Price (after subsidy) (€)	−0.0004***	−0.0003***
	(0.000)	(0.000)
ASC	−2.08**	−1.59***
	(0.842)	(0.576)
Non-Random Parameters		
Battery Life (years)	0.116**	0.051
	(0.052)	(0.031)
Top Speed (km/h)	0.006	0.007**
	(0.004)	(0.003)
Distribution of Random Parameters		
Driving range (km)	0.002	0.004***
	(0.004)	(0.002)
Battery charging time (hours)	0.152	0.198***
	(0.111)	(0.059)
Reduction in CO_2 emissions (%)	0.025**	0.002
	(0.010)	(0.006)
Plug-in hybrid back-up (Yes/No)	0.934*	1.000***
	(0.512)	(0.378)
Size (# of seats)	0.942***	0.797***
	(0.315)	(0.158)
On street parking policy (yes/no)	0.026***	0.015***
	(0.009)	(0.005)
Purchase Price (after subsidy) (€)	0.0003***	0.0002***
	(0.000)	(0.000)
ASC	1.614***	1.495***
	(0.608)	(0.386)
AIC	2126.2	
Log-likelihood function	−1027.12	
McFadden Pseudo R-squared	0.257	
Chi-squared	712.06	
Number Observations	1260	
Number of individuals	315	

Note: standard errors in parentheses. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Estimations conducted using NLogit 6 with the command *rplogit.* This is a pooled sample, single estimation; however, the results for coefficients are presented side by side for ease of comparison. The ASC belongs to the status-quo. Number of observations and number of individuals is for the full sample. A number of model specifications were tested and this table presents the model with the best fit, which is a linear model with continuous parameters.

[3] Individuals were identified by a code number (the final four digits of their mobile phone number) in order to match survey results with their responses to the first choice experiment in the previous treatment. Due to limitations in logistics we could not guarantee that each individual would get exactly the same block of choice sets they received in the first treatment, however the list of attributes, levels and design remained identical.

[4] 23 responses were omitted due to missing information.

[5] Nine responses were dropped due to missing information or they could not be matched with a questionnaire answer from the first treatment and we could not ensure the respondents were present in both sessions.

results are also robust to several specifications of the model.[6] The two data sets, prior to learning and for the treatment with learning and experience, were pooled and were estimated using a dummy variable for the treatment with learning and experience.

The results show that for the case before learning and experience (column 2 in Table 3) we see that increased range, larger vehicle size and longer battery life have a positive and significant impact on individuals' utility. The purchase price is found to be negative and significant, which is in line with economic theory (increases in prices reduce individuals' utility and probability to adopt an EV). On the other hand, increased battery charging time has a negative and significant impact on utility. These results seem plausible and are consistent with the existing literature, for example [20, 46]. Results also show that having a plug-in hybrid back-up option and higher top speed were found to be non-significant. Interestingly, our environmental and policy attributes – reduction in CO_2 emissions and on-street parking respectively - were also found to be non-significant and hence they have no effect on individuals' utility. Therefore, we can say that in this case technical variables are important in the potential decision of purchasing an EV, but not the associated environmental benefits of a decrease in emissions or a policy of reduction in parking fees in public spaces.

The results after the learning and experience with the EV (which is presented in column 3 for ease of comparison) are where individuals answered exactly the same choice experiment, but after they have been exposed to the learning and experience treatment as described in the previous section. Results show that individuals continue to prefer larger electric vehicles that have a larger driving range and use a shorter time to charge the battery although the size of coefficients has changed (increasing in importance for range but decreasing for size and battery charging time). The increase in the importance of range is interesting in the context of Rauh et al. [47] where drivers who experienced an EV on a test drive were compared with more experienced EV users (>60,000 km). They find that the less experienced drivers (test drive only) had greater range anxiety than the more experienced drivers. This is consistent with our finding that a short experience increases the importance of range, although, in light of the results of [47] it may be the case that this importance diminishes with longer 'experience' times. Range was also highlighted as a key factor in Skippon and Garwood [48] who found that following a brief driving experience (10 miles on a predefined route) participants were willing to pay a premium for an electric vehicle (over an equivalent ICE) if the EV had greater range, a result supported by a randomised controlled trial by the same authors [49].

It is seen that "top speed" becomes a significant attribute with a positive sign following 'learning and experience', which means that people prefer EVs that have higher top speeds. It is plausible that when the participants had the opportunity to briefly experience the car and see the range of the actual speedometer in the vehicle, this attribute became more important for them. This finding is interesting and supports Jensen et al. [11] who found in a demonstration trial that preferences for both top speed and range became more important following longer experience with the vehicle. We also see that battery life has become non-significant after the learning and experience session. Finally, price presents the expected negative sign.

Interesting, the environmental attribute (reductions in CO_2 emissions) gains significance, indicating that after individuals are presented with the information about the car and have had a brief experience with it, they now appreciate the environmental benefits of the electric vehicle. It is perhaps the case that the complexities of how electric vehicles contribute to CO_2 reductions became clearer to respondents following the information session, and thereby increased the value they place on this attribute.

Comparing the results in columns 2 and 3, we see that the learning and experience of EVs has altered the size and significance of a number of key attributes and therefore has affected the preferences in some way.

We find the possibility of a hybrid back-up and the policy measure are non-significant both before and after 'learning and experience'. This is notable, particularly given results in Ref. [50] where consumer preferences in China were examined and the authors found that consumers value hybrid vehicles over electric vehicles.

Thus, in summary, we find evidence that the processes of learning and experience of the good (EV) affects preferences and the ranking of attributes. It is particularly interesting to see how this process impacted the importance of the environmental benefits (CO_2 reductions) where it is seen that this attribute becomes significant after treatment. This is consistent with [51] who find that practical short term (24hr) experience with electric vehicles has the potential to change the evaluation of electric vehicle attributes and psychological factors relevant for determining behavioural intentions.

The analysis of the random parameters estimated show that there is unobserved heterogeneity in preferences between individuals. This heterogeneity is also affected by our treatment, we observe a slight increase in unobserved heterogeneity of parameters after the 'learning and experience', indicating that when participants were given more information, their preferences varied more.

Using the parameters from the model estimated above, we calculated the marginal willingness to pay (WTP) for each of the attributes considered in our choice experiment. Results are presented in Table 4.

It is interesting to note that marginal WTP for a number of the vehicle's attributes (range, charging time, and size) increases in absolute terms after individuals are exposed to our treatment of learning and experience. In order to evaluate whether these differences are statistically significant we calculated the standard errors and 95% confidence

Table 4
Marginal Willingness to pay (in Euro).

ATTRIBUTE	Choices without learning and experience	Choices with learning and experience
Driving range (per extra km)	11.04*** (5.24–16.84)	21.30*** (15.24–27.36)
Battery charging time	−344.29*** (-620.55 to −68.03)	−324.83*** (-599.56 to −50.09)
Reduction in CO_2 emissions (per 1%)	10.70 (-18.60–39.99)	32.19*** (8.07–56.31)
Plug-in hybrid back-up	−861.08 (-2240.32–518.16)	256.60 (-1026.66–1539.87)
Size	3425.84*** (2291.63–4560.04)	3486.05*** (2511.48–4460.61)
On street parking policy (per % reduction in public parking price)	−14.49 (-56.15–27.16)	6.85 (-30.87–44.57)
Battery life (per year)	332.34*** (80.70–583.97)	192.39 (-39.23–424.02)
Top speed (per km/h)	16.84 (-6.12 – 39.80)	25.95** (6.07–45.82)

Note: *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level; 95% confidence intervals in parenthesis. The marginal willingness to pay was calculated on the pooled sample but results are presented side-by-side here for ease of comparison. Estimations conducted in Nlogit 6 using the command *wald.*

[6] Robustness checks were conducted by estimating several model specifications and checking the stability of both the random and non-random parameters (significance and sign). We obtained consistent results to different specifications. Results of the alternative model specifications are available upon request.

level intervals for each welfare measure using the Wald command in NLogit.[7] Results are presented in parenthesis in Table 4 and show that for all attributes the confidence intervals overlap, indicating that differences are not statistically significant.

Considering the results from our treatment with learning and experience we can observe that individuals are willing to pay over €21 per extra kilometre of driving range in the car. They are willing to pay €325 for each hour of reduction in charging time for the battery and €26 for an increase in top speed. On the environmental attribute, we see that they are willing to pay €32 for each percentage reduction in CO_2 emissions. In addition, the marginal willingness to pay for having extra seating capacity is very high, ascending to €3486 per extra seat (size). It is important to also note that before individuals were exposed to information and experience they were willing to pay €332 for an extra year of battery life.

4.1. Limitations and future work

It should be noted that this study used a convenient sample of university students which does not represent the population as a whole, thus further work is recommended with a representative sample before policy recommendations can be inferred from this work. In relation to the discrete choice experiment, given the paper-based nature of this survey, it was not possible to personalise attributes based on participant's individual characteristics, for example, what car they currently own. Future work using online surveys could include this personalised element.

Likewise, there are other characteristics of electric vehicles which we could not test here, attributes such as faster acceleration time, lower noise, and a 'smoother' driving experience could not be accurately captured in the short 'experience' the participants had with the vehicle. Similarly, the adoption of an electric vehicle may require changes in mobility patterns, for example, requiring the need to stop to charge the vehicle for considerably longer time than to refuel a conventional vehicle or anxiety over potential 'stranding' with a low battery and no convenient charging points. These aspects can only be tested with much longer EV experiences, thus, further work is required to tease out the importance of these other aspects.

While this study included some policy based measures in the discrete choice experiment there is scope for future work to expand and tailor this aspect to consider new and emerging policy instruments. Similarly, it would be interesting to disentangle the cost of the car with different types of subsidies and the impact this has on preferences and ultimately, investment.

5. Conclusions

The promotion of electric vehicles has become an important focus in global efforts to decrease CO_2 emissions in the transport sector. This paper studied whether learning by information and brief experience has an effect on preferences and welfare measures for potential buyers of electric vehicles.

We used a choice experiment to study preferences of individuals for different technical, environmental and policy attributes of EVs before and after provision of information and a brief experience with the vehicle. Our general results indicate that individuals prefer electric vehicles that are larger, have increased range and shorter battery charging times. Each of these variables were statistically significant and are consistent with existing literature in the field, while having a hybrid back-up was found to be non-significant (which is in contrast to other research).

The introduction of learning through information and a brief experience with the EVs was shown to affect preferences: first, top speed became significant in our treatment with people preferring EVs with higher top speeds; second, individuals preferred EVs with longer battery life before the treatment, but this attribute became non-significant after treatment; and thirdly, the most interesting result in terms of a change of preferences is shown in the environmental attribute.

Our results indicate that the significance of the environmental component becomes apparent following treatment. Although the 'before learning' group also included this attribute, individuals seem to focus more on the vehicle characteristics than the environmental benefits prior to learning and experience. However, after the learning and experience treatment, the CO_2 reduction attribute became significant. The impact of electric vehicles on CO_2 emissions is a complex issue and depends on the characteristics of the underlying power system and the times of the day when the vehicle is charged. It is possible that participants were able to comprehend this relationship more clearly following the presentation from the electricity utility representative which increased the salience of this attribute in their decision making.

This latter finding also suggests that policies to increase adoption of EV should explain how the environmental benefits of EVs are determined in simple terms (and perhaps highlight that the benefit of EVs will likely increase with a reduction in carbon intensity of the power system). It is also interesting to note that the policy attribute of reduced parking fees was not significant in both groups, indicating that when people consider the decision to purchase an EV they may focus more on the technical and environmental attributes associated with the vehicle, but not the policies, although to reduce cognitive burden we only included one policy attribute in this experiment, that of free parking. This may change when considering other policies such as permission to travel in bus lanes or reduction in toll fees and this is something which could be explored in a further study.

Thus, in summary, the learning and short-term experience of the vehicle has a small effect on preferences, but there was no significant impact on the welfare measures (willingness to pay for the attributes associated to EVs). This finding supports previous literature, which indicates that longer term, for example week-long or even month-long EV experience, may be required to significantly alter preferences. This could be made possible through initiatives such as short-term car rental/car sharing programmes like "Green Mobility", which will be introduced in Ireland in the coming years [53].

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Contribution statement

Claudia Aravena: Methodology, Software, Formal analysis, Investigation, Writing- Original draft, **Eleanor Denny**: Conceptualization, Supervision, Writing- Reviewing and Editing, Methodology, Investigation, Funding acquisition, Project administration

[7] The Wald command is based on the Krinsky and Robb method in which the "marginal effects are computed as a function of the beta coefficients and the vector of means of the sample data" [52]. This technique comprises sampling *R* draws from the asymptotic normal distribution of the estimator which is then used to compute the WTP function and the associated variance, which is used to construct the confidence intervals.

Data availability

The dataset related to this article can be found at https://www.eleanordenny.org/datasets.

Declaration of competing interest

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

Appendix A

Table A1
Sample summary statistics

	Mean	Std Dev	Min	Max
Age	20.56	6.79	17	64
Highest level of Education:	**% of respondents**			
Primary School	0%			
Secondary School	94%			
Bachelor Degree	3%			
Masters Degree	0%			
PhD	0%			
Other	3%			
Female	61%			
Share of EVs choices in survey 1	89.5%			
Share of EV choices in survey 2	90.5%			

References

[1] International Energy Agency (IEA). World energy outlook. Paris: OECD/IEA; 2008.
[2] Hedenus F, Karlsson S, Azar C, Sprei F. The transportation energy carrier of the future. System interactions between the transportation and stationary sectors in a carbon constrained world. In: Proceedings of EVS24. Stavanger; 2009. May 13-166, 2009.
[3] Helmers E, Marx P. Electric cars: technical characteristics and environmental impacts. Environ Sci Eur 2012;24:14.
[4] Krupa J, Rizzo D, Eppstein M, Lanute DB, Gaalema D, Lakkaraju K, Warrender C. Analysis of a consumer survey on plug-in hybrid electric vehicles. Transport Res Pol Pract 2014;64:14–31.
[5] Lopes Mafalda Mendes, Moura Filipe, Luis M, Martinez. A rule-based approach for determining the plausible universe of electric vehicle buyers in the Lisbon Metropolitan Area. Transport Res Pol Pract 2014;59:22–36.
[6] Poullikkas A. Sustainable options for electric vehicle technologies. Renew Sustain Energy Rev 2015;41:1277–87.
[7] White L, Sintov N. You are what you drive: environmentalist and social innovator symbolism drivers electric vehicle adoption intentions. Transport Res Pol Pract 2017;99:94–113.
[8] Carley S, Krause RM, Lane BW, Graham JD. Intent to purchase a plug-in electric vehicle: a survey of early impressions in large US cites. Transport Res Transport Environ 2013;18:39–45.
[9] Hoen A, Koetse MJ. A choice experiment on alternative fuel vehicle preferences of private car owners in The Netherlands. Transport Res Pol Pract 2014;61. 199-125.
[10] Cirillo C, Liu Y, Maness M. A time-dependent stated preference approach to measuring vehicle type preferences and market elasticity of conventional and green vehicles. Transport Res Pol Pract 2017;100:294–310.
[11] Jensen AF, Cherchi E, Mabit SL. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transport Res Transport Environ 2013; 25:24–32.
[12] Franke T, Krems JF. What drives range preferences in electric vehicle users? Transport Pol 2013;30(1):56–62.
[13] Mukheerjee SC, Ryan L. Factors influencing early battery electric vehicle adoption in Ireland. Renew Sustain Energy Rev 2020;118:1–12.
[14] Glerum A, Stankovikj L, Themans M, Bierlaire. Forecasting the demand for electric vehicles: accounting for attitudes and perceptions. Transport Sci 2014;48(4): 483–99. https://doi.org/10.1287/trsc.2013.0487. Available at:.
[15] Ewing G, Emine S. Assessing consumer preference for clean-fuel vehicles: a discrete choice experiment. J Publ Pol Market 2000;19(1):106–18.
[16] Hidrue M, Parsons G, Kempton W, Gardner M. Willingness to pay for electric vehicles and their attributes. Resour Energy Econ 2011;22:686–705.
[17] Caulfield B, Farrell S, McMahon B. Examining individuals preferences for hybrid electric and alternatively fuelled vehicles. Transport Pol 2010;17(6):381–7.
[18] Bolduc D, Boucher N, Alvarez-Daziano R. Hybrid choice modeling of new technologies for car choice in Canada. Transport Res Rec 2008;2082(1):63–71.
[19] Hackbarth A, Madlener R. Consumer preferences for alternative fuel vehicles: a discrete choice analysis. Transport Res Transport Environ 2013;25:5–17.
[20] Potoglou D, Kanaroglou PS. Household demand and willingness to pay for clean vehicles. Transport Res Transport Environ 2007;12(4):264–74.
[21] Wolbertus R, Kroesen M, van den Hoed R, Chorus CG. Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: natural and stated choice experiments. Transport Res Transport Environ 2018;62:283–97.
[22] Guerra E, Daziano R. Electric vehicles and residential parking in an urban environment: results from a stated preference experiment. Transport Res Transport Environ 2020;79:102222.
[23] Qian L, Grisolia J, Soopramanien D. The impact of service and government-policy attributes on consumer preferences for electric vehicles in China. Transport Res Pol Pract 2019;122:70–84.
[24] Adler T, Wargelin L, Kostyniuk L, Kalavec C, Occiuzzo G. Incentives for alternate fuel vehicles: a large-scale stated preference experiment. In: 10th. International conference on travel behaviour research. Lucerne; 2003.
[25] Rezvani Z, Jansson J, Bodin J. Advances in consumer electric vehicle adoption research: a review and research agenda. Transport Res Transport Environ 2015;34: 122–36.
[26] Mukherjee SC, Ryan L. Factors influencing early battery electric vehicle adoption in Ireland. Renew Sustain Energy Rev 2020;118:109504.
[27] Plott CR, Zeiler K. The willingness to pay-willingness to accept gap, the "endowment effect", subject misconceptions, and experimental procedures for eliciting valuations. Am Econ Rev 2005;95:530–45.
[28] Cooper JC, Hanemann M, Signorello G. One-and-one-half-bound dichotomous choice contingent valuation. Rev Econ Stat 2002;84:742–50.
[29] Aravena C, Hutchinson G, Carlsson F, Matthews D. Testing preference formation in learning design contingent valuation using advance information and repetitive treatments. Land Econ 2018;94:284–301.
[30] Messagie M. Life cycle analysis of the climate impact of electric vehicles. J Life Cycle Assess 2014;14.
[31] McCarthy R, Yang C. Determining marginal electricity for near-term plug-in and fuel cell vehicle demands in California: impacts on vehicle greenhouse gas emissions. J Power Sources 2010;195(7):2099–109.
[32] Bahamonde-Birke FJ. Who will bell the cat? On the environmental and sustainability risks of electric vehicles. Transport Res Pol Pract 2020;133(C):79–81.
[33] Foley A, Tyther B, Calnan P, Ó Gallachóir B. Impacts of Electric Vehicle charging under electricity market operations. Appl Energy 2013;101:93–102.
[34] Sustainable Energy Authority of Ireland. Energy in Ireland 2019 report. Available: http://www.seai.ie/publications; 2020.
[35] Winter outlook 2017/18. Eirgrid. 2017. Available, http://www.eirgridgroup.com/site-files/library/EirGrid/Winter-Outlook-2017-18.pdf.
[36] Electric Vehicle Database. Nissan Leaf battery electric vehicle. 2020. https://ev-database.org/car/1106/Nissan-Leaf. [Accessed 15 July 2020].
[37] European Environment Agency. Average carbon dioxide emissions from new passenger cars. url 15th July 2020, https://www.eea.europa.eu/data-and-maps/daviz/average-emissions-for-new-cars-5#tab-chart_1; 2020.
[38] Louviere JJ, Hensher DA, Swait JD. Stated choice methods: analysis and applications. Cambridge: Cambridge University Press; 2000.
[39] Alpizar F, Carlsson F, Martinsson P. Using choice experiments for non-market valuation. Econ Issues 2003;(8):83–110.
[40] Lancaster KJ. A new approach to consumer theory. J Polit Econ 1966;74:132–57.
[41] McFadden D. Conditional logit analysis of qualitative choice behavior. Frontiers in econometrics 1974;8:105–42.
[42] Bunch DS, Louviere JJ, Anderson D. A comparison of experimental design strategies for choice-based conjoint analysis with generic-attribute multinomial

logit models. University of California Davis Graduate School of Management Working Paper; 1996.
[43] Train K. Discrete choice methods with simulation. New York: Cambridge University Press; 2003.
[44] Liao F, Molin E, Van Wee B. Consumer preferences for electric vehicles: a literature review. Transport Rev 2017;37:252–75.
[45] Achtnicht M. German car buyers' willingness to pay to reduce CO2 emissions. Climatic Change 2012;113:679–97.
[46] Chen C, Zarazua de Rubens G, Noel J, Sovacool B. Assessing the socio-demographic, technical, economic and behavioural factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. Renew Sustain Energy Rev 2020;121 [forthcoming].
[47] Rauh N, Franke T, Krems J. Understanding the impact of electric vehicle driving experience on range anxiety. Hum Factors: J Human fact Ergonomics Soc 2014;57 (1):177–87.
[48] Skippon S, Garwood M. Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance. Transport Res Transport Environ 2011;16(7): 525–31.
[49] Skippon S, Kinnear N, Lloyd L, Stannard J. How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: a randomised controlled trial. Transport Res Pol Pract 2016;92:26–42.
[50] Qian L, Soopramanien D. Heterogeneous consumer preferences for alternative fuel cars in China. Transport Res Transport Environ 2011;16:607–13.
[51] Schmalfuß F, Mühl K, Krems J. Direct experience with battery electric vehicles (BEVs) matters when evaluating vehicle attributes, attitude and purchase intention. Transport Res F Traffic Psychol Behav 2017;46(Part A):47–69.
[52] Greene W. NLogit – version 5 – reference guide. Econometric Software, Inc; 2012.
[53] Irish Times. New car sharing scheme to put 400 all-electric cars on Dublin streets. Available: https://www.irishtimes.com/business/transport-and-tourism/new-car-sharing-scheme-to-put-400-all-electric-cars-on-dublin-streets-1.3781787; 2019.