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Public Attitudes towards Electric Vehicle adoption using Structural Equation Modelling

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Abstract

This paper aims to analyse the public attitudes towards Electric Vehicles (EV) and to explore barriers in adoption of Electric vehicles in UK. The survey data was obtained from UK Data Service regarding public attitudes towards EV which possesses 1800 plus sample population. Previous research regarding recent technological development in EV field, market deployment and penetration studies, and public attitudes in different countries, were used to inform the development of model mechanism on how public adopt EV. We identify the correlation of diverse groups of consumers with various socio-economic and attitudinal barriers encountered in EV adoption. Data was analysed by Structural Equation Modelling (SEM) approach establishing the link between travel behaviour, car ownership and EV adoption level controlled by socio-demographic characteristics. We found that battery (range confidence), recharging infrastructure and technology (unreliability) can be considered as major indicators in influencing EV adoption. We also found that resale value, environmental performance and recharging infrastructure are the major enablers of EV adoption. Perhaps none of these findings are new to many but the implication that this study has brought is the fact that general UK public is far from EV realm and more has to be done before the ban of internal combustion engines taken place in 20 years from now.

*Keywords:*Electric vehicles; UK market; Travel behaviour; Structural equation models

1. Introduction

Greenhouse gas emission (GHG) has been regarded as the major threat for climate change and global warming. According to 2015 statistics, transport sector contributes approximately 24% of the total GHG emission in UK.

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Carbon dioxide (CO_2) is the most significant greenhouse gas, accounting 81% of total UK GHG emissions, 75% of which is generated by road transport (Department of Energy and Climate Change *DECC*, 2015). UK has introduced Climate Change Act in 2008, in accordance with signing the Paris agreement, to counter climate change by developing a low carbon economy. According to this act, regulation has targeted to reduce GHG emissions at least by 80% to 2050 with an intermediate target of reducing GHG emissions at least by 34% to 2020 compared to 1990 emissions levels (Parliament of the United Kingdom, 2008). Thus, UK government is focusing on decarbonizing the road transport, which is a major contributor of greenhouse gases, by granting investment funds on emerging fuel-efficient and low emissions technologies. In this scenario, Electric vehicles (EV) are considered as a potential solution for achieving low CO_2 emissions targets, as electricity is generated from renewable energy sources. There is no exhaust pipe or generation of harmful particulates in electric vehicles and reduced CO_2 emissions, even when accounting for charging and battery production.

Popularity of EV adoption studies globally (reviewed by Rezvani, Jansson, & Bodin, 2015 and Liao, Molin, & van Wee, 2017) has not been receiving the same level of popularity among general consumer to adopt EV as the choice of vehicle. With the exception of Norway, which has high EV market share of over 20%, and the Netherlands with over 2%, the rest of other countries and beyond are still catching up to get even 1% (Berkeley, Jarvis, & Jones, 2018). Reasons for slow growth for many are varied and some governments are getting aggressive in boosting the growth. UK is one of the first countries to gear EV adoption through banning production and sales of internal combustion engines vehicles in the next 15-20 years from today. With this in mind, it is clear that we have to do reality check with what general people think of EV adoption and this is especially the case of the UK. This paper is addressing just that; we use recent UK national statistics survey data to understand the relationship between travel behaviour, socio-economic, socio-demographic and the attitude towards EV adoption. Unlike many studies on EV adoption which uses targeted sample to understand behaviour towards EV adoption, we rather uses revealed preference data to demonstrate the real situation of perceived EV consumer market.

Nomenclature

EVs	Electric vehicles
BEVs	Battery electric vehicles
ICE	Internal combustion engine
SEM	Structural equation modelling
GHGs	Greenhouse gases
AMOS	Analysis of moment structures

2. Literature review

2.1 State of knowledge EV adoption

Investigating consumer insight towards EV is essential in elaborating factors influencing purchasing behaviour and motivation in order to obtain the appropriate strategy, which will enable EV market penetration. There is wide range of factors that affect EV uptake. The methodology of past EV adoption studies are outlined as follows:

Ozaki & Sevastyanova (2011) utilizes binary factor analysis on survey data of 1263 respondents based in London, who had purchased Toyota Prius (Hybrid EV) in last 24 months, to conclude that UK transport policy and financial incentives play significant role in decision making for switching to hybrid vehicle. For example, congestion charge exemption upon driving in central London area had remarkable influence on respondents. This study also pointed out that apart from government policies, other EV uptake influencing factors are environmental benefits due to low emissions, comfort of driving, reliability and economic benefits due to less fuel utilization and lower running costs.

Egbue & Long (2012) utilizes chi-square analysis on a survey data of 481 technology enthusiasts, to conclude that travel range is the most significant factor which is limiting EV uptake followed by high purchasing cost and charging infrastructure. Although in this study majority of the respondents are reported to travel less than 40 miles daily.

Degirmenci & Breitner (2017) utilizes structural equation modelling (SEM) on survey data of 167 participants in test driving an BEV, and outcomes of limiting EV uptake factors are the expensive purchase cost, insufficiency and long recharge duration of charging infrastructure and limited travel range. Participants emphasize the importance of renewable energy share of electricity generation to determine the effectiveness of EV transition (Degirmenci & Breitner, 2017).

Larson, Viáfara, Parsons, & Elias (2014) utilizes willingness-to-pay and van Westendorp price sensitivity (PSM) on a survey data of 240 respondents, which consists of experienced EV users, students and public. The study findings conclude that the most important factors that affect the respondents' decision on EV uptake are purchase price and travel range. Other significant factors include provision of charging points and usage convenient. Other outputs of this points out that respondents with exposure to EVs tend to show greater willingness to pay for EV, majority of the respondents emphasize the importance of renewable energy share on encouraging them of EV uptake and finally PSM analysis shows that the average acceptable purchase cost of EV ranges between $22,000-27,500 Canadian dollars, which is equivalent to £13,471-£16,839.

Axsen, Orlebar, & Skippon (2013) utilized ordinal logistic regression analysis on responses resulted from interviewing of 21 staffs in a technology-based workplace, which eight staffs 19 experienced a test-drive in BEV, eight staffs experienced as a passenger and remaining five staffs without experiencing the test-drive event. The findings of the studies shows that encourage factors for EV uptake are environmental benefits, savings on fuel economy, comfort in terms of quietness and smoothness in vehicle performance and the ability to recharge the vehicle at home. While the discouragement of EV uptake of the staffs are limited travel range, high purchase cost and provision of charging points. As the perception towards EV of the staffs are highly influenced by inexperienced individuals, hence shows that misperception towards EV is a major barrier in EV adoption.

Wang, Yu, Yang, Miao, & Ye (2017) conducted an analysis on 406 public familiar with EVs using several statistical methods including factor analysis, chi-square analysis, the Fisher's test and two-way frequency tables to obtain the findings that the main factors affecting the widespread adoption of EV are limited provision of charging points, purchase and operating cost, travel range and misperception of EV technology. Average acceptance of the purchase price of EV shows 50% respondents expected EV price ranges between $13,071-$24,509 US dollars, equivalent to £9,950-£18,693 and 37.3% respondents expected EV price ranges between $24,509-$40,849 US dollars, equivalent to £18,693-£31,154. This study also revealed that the exposure of consumers towards the knowledge of innovation is vital and business communities should emphasize on promoting the EV technology.

Jensen, Cherchi, & Mabit (2013) utilized willing-to-pay method and Monte Carlo simulation on survey data, consisting of 369 households, before and after experiencing an EV in a three-month period. The outputs of the study is that the major factor that affect the respondents' EV uptake is the limited travel range and other minor factors including EV performance, charging points provision and high purchase cost, and also that the respondents' perception towards EV do change and show higher willingness to pay after having experience on driving an EV.

Knez, Jereb, & Obrecht (2014) utilizes K-means cluster analysis and principal component factor analysis on a survey data of 681 public respondents and identifies that the main factors affecting the consumers' choice on EV uptake are purchase cost, safety feature and fuel economy, and it also found that 30% reduction of purchase cost would lead to 59% serious consideration of purchasing an EV by consumers.

From the above studies, barriers to EV adoption maybe understood to derive primarily from aspects that can be categorised as economical, technological (including infrastructure) and psychological. This conclusion is echoing many of the recent review of EV adoption studies (see for example: Liao et al., 2017 and Berkeley et al., 2018). Efforts to improve the consumer's anxiety towards the above aspects would be needed to increase EV adoption. We particularly pay attention to a German data study by Degirmenci & Breitner (2017) which has successfully established a mechanism of EV adoption decision controlling socio-economic and demographic variables to a segmented population. With our paper we aim to establish the decision making mechanism of EV adoption of the UK market.

2.2. UK transport policies for promoting EV adoption

According to UK government 2017 plan to tackle roadside NO_2 concentrations published by Department for Environment, Food & Rural Affairs, and Department for Transport (Coffey, & Gove, 2017), Britain will ban all new petrol and diesel cars and vans from 2040. As these vehicle are responsible for rising levels of NO_2, thus possessing major risk for public health. Research carried out by DEFRA estimated that the total impact of poor air quality on productivity of country costed £2.7 billion in 2012. Therefore targets £2.7 billion funding to improve the air quality situation. This funding comprises of £1 billion on Ultra low emissions vehicles that includes investing around £100million in the UK's charging infrastructure and funding the Plug in Car and Plug in Van Grant Schemes. Additionally, £290 million was invested as National Productivity fund, for reducing greenhouse gases emissions in transport sector. This includes £100 million for new buses, and retrofit, £50 million is awarded for Plug in Taxi programme and £80 million for ULEV charging infrastructure.

In order to make public transportation green, UK Government has launched Green Bus Fund in 2010 and Clean Bus Technology Fund scheme in 2015. Under Green Bus Fund, government has invested £89 million to support bus companies and local authorities in England to introduce 1200 new low carbon buses on the roads. Since 2013, Government has granted £27 million to retrofit almost 3,000 of old vehicles, which mainly consists of buses as a part of Clean Bus Technology Fund and Clean Vehicle Technology Fund. Moreover, in July 2017, £40million is made available for Clean Bus Technology Fund grant scheme as part of National productivity fund (discussed above), to retrofit 2350 older buses (Department for Environment et al., 2017)

National Statistics Report (Evans, 2018) outlines progress in UK electricity generation in first quarter of 2018 as compared to first quarter of 2017:

- Total renewable energy (from wind, solar, hydro and bioenergy) share increased to 30.1% from 27%.
- Fossils fuel (from coal, gas, oil and others) share decreased to 52% compared to 54.2%, resulting specifically from a drop in coal to 9.4% from 11.1%, and a similar drop in gas by 0.6%.
- Low carbon electricity (from nuclear and renewable sources) increased to 48% from 45.8%, resulting mainly due to the increment in wind capacity.

Above policies demonstrates actions by the UK government to create market transition from Internal Combustion Engines (ICE) powered vehicles to EV. Without clear understanding on current market response to EV adoption, it is unclear how to prioritise the investments to leverage change. We aim to address this gap with this paper.

3. Methodology

3.1. Data

The survey data from the UK Data Service is obtained which comprises of face-to-face interview responses. These interviews were administrated by Office for National Statistics (ONS) interviewers, who were professionally trained for conducting the process. Face-to-face interviews present more accurate data than telephonic interviews and online surveys as telephone respondents are more suspicious about the interview process and more likely to present themselves in socially desirable ways when compared to face-to-face respondents (Green, Krosnick, & Holbrook, 2001). Furthermore, the survey data was collected by random selection of 67 postal sectors that has covered the whole Great Britain to ensure a representative sample and choosing 30 respondents from each postal sector depicting their own household in each month, accounting to 2010 addresses. Data of both years i.e. 2014-15 are combined for analysis, however only 1851 units were considered for inclusion due to incompleteness of the survey from some respondents and excluding the responses such as “do not know” and “refusal”. Data categories are sufficient to cover the subsequent division and analysis in order for conclusions of this study to be reliable. Section 4 describes descriptive statistics of the sample.

3.2 Methodology of structural equation modelling

In reviewing many papers on EV adoption, despite clear narration of many identified challenges and barriers, we found that very little is known of the decision making mechanism during EV adoption. But this is perhaps due to the very few available data around that uses real EV adopters as also confirmed by (Liao et al., 2017). We find that the German data study by Degirmenci & Breitner (2017) is one of the first to explore the mechanism of decision making on EV adoption towards socio-economic and demographic variables and attitudinal attributes related to EV. In our paper, we employ similar apporach on UK data through the use of SEM.

SEM first emerged in 1970s with its application in psychology, sociology, market research and educational research areas. SEM’s use in travel behaviour research study dates back to 1980s (Golob, 2003). The use of SEM via different approaches has been evolved over the years, but currently two approaches of covariance analysis method are widely used: 1) LISREL (Linear Structural Relations) and 2) AMOS (Analysis of Moment Structures) (Westland, 2015).

SEM is a modelling technique which identify latent (unobserved) variables underlying a group of observed variables and structural equations, which represents directional relationship between latent and observed variables (Aditjandra, Cao, & Mulley, 2012). SEM can demonstrates direct effect of one variable on other, which is represented by a unidirectional arrow in a path diagram. Indirect effects can be illustrated through mediating variable, such influence of travel distance on mode choice behaviour through availability of new mode of transport. In above case, availability of new transport mode is termed as mediating variable. SEM can also separate errors in equations from errors in measurement, and it allows correlation of error terms within all types of errors (Golob, 2003).

In comparison to other multivariate analysis methods, structural equation models allow the explorations of interrelations between variables in multiple stages. Unlike regression modelling, SEM allows simultaneous evaluation of model construct relationships using covariance analysis and measurement error is not aggregated in a residual error term (Chin, 1998). It can handle multiple endogenous variables with interdependent relations among them, and the incorporation of intervening variables that can simultaneously be exogenous and endogenous in nature (Scheiner & Holz-Rau, 2007). SEM also enables to estimate bi-directional relationship between variables, which is termed as feedback loops, contrary to regression that allows only unidirectional relationship.

Maximum likelihood estimation (MLE) is used to develop the structural equation model. According to simulation studies conducted by (Golob, 2003), the maximum likelihood approach is proved robust against the violation of normal distribution assumption, at least for large samples. The analysis of this study is carried out using IBM SPSS Amos 25 version that is available with a user-friendly graphic surface. The main purpose of utilizing SEM in this study is to investigate the correlation between socio demographic profiles of respondents with their attitudes towards EV.

Firstly, covariance matrix between variables is computed in SEM process, following which parameters in path diagram are calculated such that the empirical covariance matrix is reconstructed to be commensurable. The difference between the modelled matrix and empirical matrix is measured through significance tests. Although the significance test considers the assumption of multivariate normal distribution of observed variables, such an assumption is often contradicted in practice (Scheiner & Holz-Rau, 2007). According to the Normality test conducted in preliminary analysis section of this study, it can be concluded that survey dataset is not normally distributed. However, if the

Table 1: Descriptive analysis table of data sets

Variable	Category		Frequency	Percentage
Socio demographic variable				
Age	16-24 (Teenagers and young adults)		144	7.8
	25-44 (Adults)		552	29.9
	45-54 (Middle aged adults)		305	16.5
	55-64 (Old adults)		325	17.6
	65-74 (Old adults)		321	17.4
	75+ (Old adults)		202	10.9
Gender	Male		871	47.1
	Female		978	52.9
Home Ownership	Own Outright		649	35.1
	Own Mortgage		583	31.5
	Rents privately		273	14.8
	Rents from Local Authority/House Association		344	18.6
Household size	One		531	28.7
	Two		694	37.5
	Three		287	15.5
	Four		233	12.6
	Five or more		104	5.6
Gross Annual Income	No income		81	4.4
	Less than £10,400		555	30.0
	£10,400 - £20,799		547	29.6
	£20,800 - £38,999		380	20.6
	£39,000 - £49,399		82	4.4
	£49,400+		123	6.7
	Refusal		81	4.4
Education Level	Degree or equivalent		454	24.6
	Below degree level		812	43.9
	Other qualifications		204	11.0
	None		379	20.5
Employment Status	In employment		988	53.4
	Unemployed		89	4.8
	Economically inactive		772	41.8
Attitudinal variables				
Important factors considered while buying a car	Environment friendly	Yes	1355	73.3
		No	494	26.7
	Cost	Yes	833	45.1
		No	1016	54.9
	Electrification	Yes	668	36.1
		No	1181	63.9
	Style/Design	Yes	88	4.8
		No	1761	95.2
	Interior space	Yes	545	29.5
		No	1304	70.5
	Reliability (Travel range)	Yes	599	32.4
		No	1250	67.6
	Safety	Yes	1233	66.7
		No	616	33.3
	Speed/performance	Yes	1028	55.6
		No	821	44.4
Put off factors regarding EV adoption	Lack of knowledge	Yes	143	7.7
		No	1706	92.3
	Cost	Yes	237	12.8
		No	1612	87.2
	Battery Range	Yes	477	25.8
		No	1372	74.2

	Recharging	Yes	579	31.3
		No	1270	68.7
	Resale value	Yes	640	34.6
		No	1209	65.4
	Safety	Yes	36	1.9
		No	1813	98.1
	Speed/performance	Yes	46	2.5
		No	1803	97.5
	Technology (Unreliable)	Yes	141	7.6
		No	1708	92.4
Encourage factors regarding EV adoption	Recharging	Yes	287	15.5
		No	1562	84.5
	Resale value	Yes	260	14.1
		No	1589	85.9
	Safety	Yes	36	1.9
		No	1813	98.1
	Performance	Yes	56	3.0
		No	1793	97.0
	More choice	Yes	90	4.9
		No	1759	95.1
	Technology (Reliable)	Yes	58	3.1
		No	1791	96.9
	Environment friendly	Yes	121	6.5
		No	1728	93.5

Revealed travel behaviour			
Frequency of using Public Transport Use	At least once a day	199	10.8
	Less than once a day but at least once or twice a week	192	10.4
	Once or twice a week	223	12.1
	Less than once a week but more than twice a month	109	5.9
	Once or twice a month	201	10.9
	Less than once a month but more than twice a year	303	16.4
	Once or twice a year	267	14.4
	Less than once a year or never	355	19.2
Frequency of Private Car Use	At least once a day	889	48.1
	Less than once a day but at least once or twice a week	372	20.1
	Once or twice a week	246	13.3
	Less than once a week but more than twice a month	84	4.5
	Once or twice a month	79	4.3
	Less than once a month but more than twice a year	65	3.5
	Once or twice a year	37	2.0
	Less than once a year or never	77	4.2
Car Ownership	Zero car	451	24.4
	One car	803	43.4
	Two cars	472	25.5
	Three or more cars	123	6.7
Levels of EVs adoption			
EV purchase decision	Own an EV	4	0.2
	Thinking to own an EV	76	4.1
	Wanted before	270	14.6
	Never wanted to	1055	57.1
	Do not drive	357	19.3
	Do not know	87	4.7

sample size is considerably large for a dataset, then the effects of this contradiction is considered as negligible.

The results generated from the sensitivity analysis (Bagley & Mokhtarian, 2002) indicated that outputs from the model meeting the assumption of multivariate normality were almost identical to results of prior model, with large sample that did not fulfil the criteria of the assumption. Therefore, the alternative of transforming observed variables with skewed distribution, either by taking square root or natural log, is rejected in order to sustain the original values that can be interpreted conveniently.

4. Descriptive analysis and modelling results

4.1. Descriptive analysis

Data in the study includes 10 socio-demographic variables describing demographic profile of individuals and their travel behaviour, and 24 attitudinal variables explaining public attitudes towards EV. In addition to listing of variables, this table also include frequency distribution and percentage split of each variable category as shown in table 1

Descriptive analysis in this study shows the soundness of sample group and corresponding patterns among responses. Respondents' proportion among age and gender categories represents even distribution; there is also good stability throughout employment, income and travel behaviour attitudes i.e. frequency of using private vehicle and public transportation. There is variety of responses in terms of attitudes towards EV, with only four individuals owning an EV and major proportion never wanted to have one. If put off factors and encourage factors are considered for EV, mostly respondents answered 'No' for each variable.

Additionally, the data incorporates an even proportion of socio-demographic categories; thus covering all sectors of society. There is a relatively low proportion of respondents having a positive attitude towards EV. Hence, this study will be helpful in investigating reasons behind public unwillingness to pay for EV. A significant amount of respondents do not drive and own a vehicle, which might results in underestimation of percentage in terms of current EV users and diesel car users who might own EV in future, as it is important to evaluate respondents who have driving experiences to improve credibility of the study. Therefore, descriptive analysis is able to identify the limitation related to dataset as the phenomena mentioned above can lead to aberration from actual observation.

4.2. Model estimation and analysis

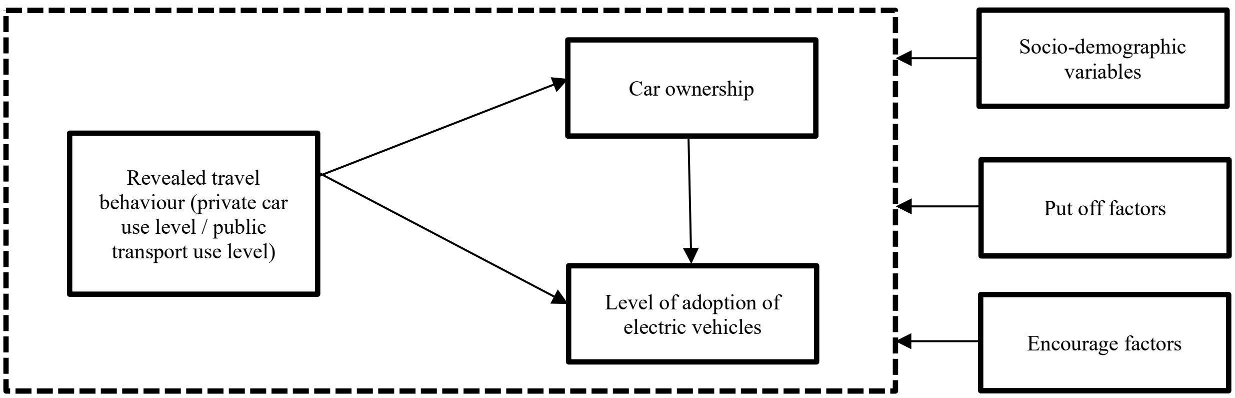

Fig 1. Conceptual model

One of the most important aspect of developing an SEM is modeling the conceptual framework of how the behaviour change can be evaluated and assessed. Fig 1 below demonstrating the general conceptual model of how travel behaviour change (in the form of level use of either by private car or public transport use) affecting car ownership level and influencing perceived level of EV adoption. These relationships are affected by exogenous variables such as socio-demographic and EV attitude attributes. This model is developed from the work (Aditjandra et al., 2012) and (Aditjandra, Cao, & Mulley, 2015) who have successfully established SEM models based on car drivers and public transport users.

Four SEM models were developed to represent 4 scenarios of perceived EV adoption: the first one is public transport users' model which are affected by either EV attitude on put off factors (Model 1) or encourage factors (Model 2); the second one is private car user model which are affected by either put off/encourage attitudes factors (Model 3 and Model 4). The models good fit are summarized in Table 2.

Table 2*. Indicators of goodness of fit of the models

Model	CMIN	DF	CMIN/DF	GFI	CFI	NFI	RMSEA	PCLOSE	Hoelter Critical N
Encourage EV models									
Public transport usage	42.600	10	4.260	0.997	0.994	0.992	0.042	0.828	1007
Private car usage	28.817	10	2.882	0.998	0.997	0.995	0.032	0.985	1489
Put off EV models									
Public transport usage	62.182	11	5.653	0.996	0.990	0.988	0.059	0.465	735
Private car usage	74.685	11	6.790	0.996	0.988	0.987	0.056	0.191	612

**CMIN is "chi-square value" which measures the discrepancy between the sample and model-implied covariance matrices. This value depends on sample size, which increases with sample size, therefore it is not a goodness of fit measure. Although it is always reported to provide basis for other goodness of fit measures (Byrne, 2010). Df "degree of freedom" equals to the difference between the number of sample moments and the number of parameters to be estimated. CMIN/Df is a "relative chi-square value" which is corrected for Df, it can also be defined as the minimum of the discrepancy function between the sample covariance matrix and the model covariance matrix, divided by Df, with value as low as 2 or as high as 5 indicate a reasonable fit (Marsh & Hocevar, 1985). GFI (Goodness-of-fit index), does not depend on sample size and measures how much better the model fit as compared to no model at all, value greater than 0.90 indicates a good fit (Jöreskog & Sörbom, 2005). NFI (Normed fit index), measures how much better the model fits as compared to a baseline model, usually the independence model, value greater than 0.90 indicates a good fit (Bentler & Bonett, 1980). CFI (Comparative fit index) assesses the improvement of the hypothesized model compared to the independence model (Null model without any restrictions) with unrelated variables, value greater than 0.90 indicates a good fit (Bentler, 1990). RMSEA (Root mean square error of approximation) measures the estimated discrepancy between the model implied and true population covariance matrix, corrected for degree of freedoms; with values less than 0.05 indicate a good fit model, and values as high as 0.08 represent a reasonable fit. PCLOSE (p value) is the probability for testing the null hypothesis of close fit, which represents that the population RMSEA value is no greater than 0.05, therefore good fit model have PCLOSE value greater than 0.05 (Browne & Cudeck, 1992). The Hoelter critical N is the parameter to judge the adequacy of sample size. Critical N with value of 200 or greater indicates a satisfactory fit and value below 75 is unacceptable (Tanaka, 1987).*

Table 3*. Standardized total, direct and indirect effects for the Put off EV adoption model with public transport usage (Conceptual model).

Variables	Public transport usage frequency			Car ownership			Levels of EVs adoption		
	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects
Endogenous variables									
Levels of EVs adoption	0	0	0	0	0	0	0	0	0
Public transport usage frequency	0	0	0	-0.258	-0.258	0	-0.095	-0.043	-0.052
Car ownership	0	0	0	0	0	0	0.202	0.202	0
Exogenous variables									
Put off Knowledge	0	0	0	0.045	0.045	0	0.048	0.039	0.009
Put off Vehicle	0	0	0	-0.056	-0.056	0	-0.042	-0.031	-0.011
Put off Cost	0	0	0	-0.002	-0.002	0	0.016	0.017	0.001
Put off Recharging[a]	**0**	**0**	**0**	**0.073**	**0.073**	**0**	**0.105**	**0.091**	**0.015**
Put off Technology[a]	**0**	**0**	**0**	**0.059**	**0.059**	**0**	**0.059**	**0.047**	**0.012**
Put off Safety	0	0	0	0.005	0.005	0	-0.031	-0.032	0.001
Put off Battery[a]	**0**	**0**	**0**	**0.014**	**0.014**	**0**	**0.126**	**0.123**	**0.003**
Put off Resale	0	0	0	0.046	0.046	0	0.045	0.035	0.009
Gender	0	0	0	-0.017	-0.017	0	-0.086	-0.089	0.003
Age	0	0	0	0.063	0.063	0	-0.058	-0.071	0.013
Income	-0.004	-0.004	0	0.066	0.065	0.001	0.058	0.044	0.014
Employment	-0.037	-0.037	0	0.165	0.155	0.010	0.062	0.027	0.035
Education[a]	**0.079**	**0.079**	**0**	**0.097**	**0.118**	**-0.020**	**0.157**	**0.141**	**0.016**
Household size	-0.060	-0.060	0	0.338	0.323	0.016	0.063	-0.008	0.071
Home ownership	-0.163	-0.163	0	0.332	0.290	0.042	0.152	0.078	0.074

*Standardized total effects illustrate the strength of relationship between revealed travel behaviour, car ownership, levels of EVs adoption, attitudinal variables and socio demographic characteristics. Standardized total effects is the sum of standardized direct and indirect effects, e.g. in Table 3, when coefficients of public transport use impact on levels of EVs adoption is considered, -0.043 (direct effect) and -0.052 (indirect effect) sum to the value of – 0.095 (total effect). Standardized direct effects represents the immediate influence of one variable on another, while standardized indirect effects demonstrates the influence of one variable on another via mediating/intervening variable. For example, in our study car ownership is mediating variable, therefore indirect effect of public transport usage on levels of EVs adoption via car ownership is -0.052. The positive value of coefficients represents directly proportional relationship, and negative value of coefficients represents inversely proportional relationship between variables. As it can be seen from above table 3 that most of coefficients corresponds to value 0, e.g. total effects of attitudinal variables on public transport use, this is because in path diagram these attitudinal variables are not linked to public transport use variable, due to their insignificant correlation values.

[a]Variables which are marked in bold represents the most significant exogenous variables which have major influence on levels of EVs adoption.

Table 4. Standardized total, direct and indirect effects for the Put off EV adoption model with private car or van usage (Conceptual model).

Variables	Private car usage frequency			Car ownership			Levels of EVs adoption		
	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects
Endogenous variables									
Levels of EVs adoption	0	0	0	0	0	0	0	0	0
Private car usage frequency	0	0	0	0.359	0.359	0	0.175	0.114	0.061
Car ownership	0	0	0	0	0	0	0.169	0.169	0
Exogenous variables									
Put off Knowledge	0	0	0	0.027	0.027	0	0.040	0.035	0.005
Put off Vehicle	0	0	0	-0.059	-0.059	0	-0.043	-0.033	-0.010
Put off Cost	0	0	0	-0.018	-0.018	0	0.007	0.011	-0.003
Put off Recharging[a]	**0**	**0**	**0**	**0.055**	**0.055**	**0**	**0.095**	**0.086**	**0.009**
Put off Technology[a]	**0**	**0**	**0**	**0.050**	**0.050**	**0**	**0.055**	**0.047**	**0.008**
Put off Safety	0	0	0	0.008	0.008	0	-0.030	-0.031	0.001
Put off Battery[a]	**0**	**0**	**0**	**0.010**	**0.010**	**0**	**0.122**	**0.121**	**0.002**
Put off Resale	0	0	0	0.041	0.041	0	0.039	0.032	0.007
Gender	0	0	0	-0.008	-0.008	0	-0.097	-0.096	-0.001
Age	0	0	0	0.083	0.083	0	-0.054	-0.068	0.014
Income	0.057	0.057	0	0.066	0.046	0.020	0.057	0.040	0.018
Employment	0.200	0.200	0	0.176	0.104	0.072	0.065	0.013	0.052
Education[a]	**0.093**	**0.093**	**0**	**0.108**	**0.074**	**0.033**	**0.162**	**0.134**	**0.029**
Household size	0.088	0.088	0	0.346	0.315	0.032	0.064	-0.004	0.068
Home ownership	0.297	0.297	0	0.329	0.222	0.107	0.153	0.064	0.089

Table 5. Standardized total, direct and indirect effects for the Encourage EV adoption model with public transport usage (Conceptual model).

Variables	Public transport usage frequency			Car ownership			Levels of EVs adoption		
	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects
Endogenous variables									
Levels of EVs adoption	0	0	0	0	0	0	0	0	0
Public transport usage frequency	0	0	0	-0.265	-0.265	0	-0.106	-0.048	-0.058
Car ownership	0	0	0	0	0	0	0.219	0.219	0
Exogenous variables									
Encourage Environment[a]	**0**	**0**	**0**	**0.054**	**0.054**	**0**	**0.050**	**0.038**	**0.012**
Encourage Technology	0	0	0	0.012	0.012	0	0.019	0.016	0.003
Encourage More Choice	0	0	0	-0.019	-0.019	0	0.000	0.004	-0.004
Encourage Vehicle	0	0	0	-0.039	-0.039	0	0.018	0.027	-0.008
Encourage Safety	0	0	0	-0.013	-0.013	0	0.002	0.005	-0.003
Encourage Resale[a]	**0**	**0**	**0**	**0.015**	**0.015**	**0**	**0.090**	**0.086**	**0.003**
Encourage Charging[a]	**0**	**0**	**0**	**0.079**	**0.079**	**0**	**0.036**	**0.018**	**0.017**
Gender	0	0	0	-0.008	-0.008	0	-0.102	-0.104	0.002
Age	0	0	0	0.062	0.062	0	-0.064	-0.078	0.013
Income	-0.004	-0.004	0	0.067	0.066	0.001	0.057	0.042	0.015
Employment	-0.037	-0.037	0	0.167	0.157	0.010	0.070	0.032	0.038
Education[a]	**0.079**	**0.079**	**0**	**0.109**	**0.130**	**-0.021**	**0.180**	**0.160**	**0.020**
Household size	-0.060	-0.060	0	0.339	0.323	0.016	0.058	-0.019	0.077
Home ownership	-0.163	-0.163	0	0.337	0.294	0.043	0.167	0.086	0.081

Table 6. Standardized total, direct and indirect effects for the Encourage EV adoption model with private car or van usage (Conceptual model).

Variables	Private car usage frequency			Car ownership			Levels of EVs adoption		
	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects
Endogenous variables									
Levels of EVs adoption	0	0	0	0	0	0	0	0	0
Private car usage frequency	0	0	0	0.366	0.366	0	0.195	0.129	0.065
Car ownership	0	0	0	0	0	0	0.179	0.179	0
Exogenous variables									
Encourage Environment[a]	**0**	**0**	**0**	**0.041**	**0.041**	**0**	**0.041**	**0.034**	**0.007**
Encourage Technology	0	0	0	0.010	0.010	0	0.018	0.016	0.002
Encourage More Choice	0	0	0	-0.013	-0.013	0	0.003	0.005	-0.002
Encourage Vehicle	0	0	0	-0.048	-0.048	0	0.015	0.023	-0.009
Encourage Safety	0	0	0	-0.017	-0.017	0	-0.001	0.002	-0.003
Encourage Resale[a]	**0**	**0**	**0**	**0.030**	**0.030**	**0**	**0.097**	**0.091**	**0.005**
Encourage Charging[a]	**0**	**0**	**0**	**0.060**	**0.060**	**0**	**0.025**	**0.014**	**0.011**
Gender	0	0	0	-0.018	-0.018	0	-0.114	-0.111	-0.003
Age	0	0	0	0.083	0.083	0	-0.060	-0.074	0.015
Income	0.057	0.057	0	0.066	0.045	0.021	0.056	0.037	0.019
Employment	0.200	0.200	0	0.176	0.103	0.073	0.072	0.015	0.057
Education[a]	**0.093**	**0.093**	**0**	**0.116**	**0.082**	**0.034**	**0.183**	**0.150**	**0.033**
Household size	0.088	0.088	0	0.347	0.315	0.032	0.060	-0.013	0.073
Home ownership	0.297	0.297	0	0.331	0.222	0.109	0.166	0.069	0.098

The four structural equation models (SEMs) results are shown in Table 3, Table 4, Table 5 and Table 6.

Table 3 demonstrates SEM model considering attitude of ‘put off EV adoption’ on public transport users: in this model, socio demographic variables and put off factors, that are perceived as barriers towards EV adoption, are treated as exogenous observed variables, and frequency of public transport usage (revealed travel behaviour), car ownership and levels of EVs adoption are considered as endogenous observed variables.

Table 4 shows SEM model considering ‘put off EV adoption’ on private car or van users: in this model, socio demographic variables and put off factors, that are perceived as barriers towards EV adoption, are treated as exogenous observed variables, and frequency of private car or van usage (revealed travel behaviour), car ownership and levels of EVs adoption are considered as endogenous observed variables.

Table 5 shows SEM model considering ‘encourage EV adoption’ on public transport users: in this model, socio demographic variables encourage factors, that are enablers towards EV adoption, are treated as exogenous observed variables, and frequency of public transport usage (revealed travel behaviour), car ownership and levels of EVs adoption are considered as endogenous observed variables.

Table 6 demonstrates SEM model result considering ‘encourage EV adoption’ on private car or van users: In this model, socio demographic variables encourage factors, that are enablers towards EV adoption, are treated as exogenous observed variables, and frequency of private car or van usage (revealed travel behaviour), car ownership and levels of EVs adoption are considered as endogenous observed variables.

In all the above mentioned models, car ownership is treated as mediating variable between revealed travel behaviour variables, i.e. frequency of public transport usage or frequency of private car or van usage, and levels of EVs adoption. (Please see Fig 1: conceptual model). There are eight put off factors and seven encourage factors corresponding to the purchase decision of EVs from the dataset, as mentioned in descriptive analysis section (please see Table 1). The purpose of these models is to extract relevant factors, out of all put off and encourage factors variables, which are having significant influence on their corresponding level of EVs adoption attitudes, and analyze the correlation of these factors with socio demographic variables and travel behaviour. These models are also aimed to analyze the impact of travel behaviour of respondents on their EVs attitudes directly, and also indirectly through their car ownership status, which is acting as a mediating variable.

4.3. Model discussion

4.3.1. Put off factors influencing EVs adoption

Tables presented above explain the matrix of standardized total, direct and indirect effects of four EV adoption (default) models in AMOS. Dataset identifies total eight put off factors for EV adoption, out of which only three factors are found to be relevant according to the magnitude of their standardized total effects on levels of EVs adoption (endogenous) variable (Refer to Table 3 and Table 4: put off factors marked in bold). These three factors are battery (range confidence), recharging infrastructure and technology (unreliability), which can be considered as major indicators influencing of EVs adoption.

Although, before analyzing the impact of put off factors on EVs adoption, all of them are thought to have a negative correlation with levels of EVs adoption, but from our analysis it is found that only two factors which are vehicle performance (handling and practicality features) and safety features, have negative correlation with EVs adoption. Therefore these factors can be regarded as the barriers towards EVs adoption. On the other hand, three most significant factors which are battery (range confidence), recharging infrastructure and technology (unreliability) can be stated as the major indicators towards EVs adoption. Therefore, if the policy implications are to be made in future in favour of EVs, they need to be focused on these three major indicators.

Range confidence is found to be most significant factor affecting the levels of EVs adoption, 0.126 (Table 3) and 0.122 (Table 4) as standardized total effects coefficient value in both put off EV adoption models, although this factor does not have a significant relationship with car ownership i.e. 0.014 (Table 3) and 0.010 (Table 4) as total effects coefficients. Therefore it can be implied that range confidence is a major indicating factor among both private car owners and people who do not own a car, so it can be viewed as a general perception towards EVs. Our study findings of major indicators for EV adoption which is, range confidence and recharging infrastructure, resonates with the results of Egbue & Long, 2012. Third factor which is technological unreliability, corresponds to 0.059 (Table 3) and 0.055 (Table 4) as standardized total effects on levels of EVs adoption. This represents that people do not consider technology of EVs as reliable, this can due to the lack of knowledge about technological features of EVs, as most of our respondents are not EV users and most of them do not have driving experience in an EV. Therefore, in future circumstances if these people are exposed more to EVs use, this might change perceptions, beliefs and attitudes towards EVs adoption. This inclination towards EVs after having exposure, is also one of findings from Larson et al., 2014.

4.3.2. Encourage factors influencing EVs adoption

Similarly, dataset mentions total seven encourage factors for EV adoption, out of which only three factors are found to be most relevant according to the magnitude of their standardized total effects on levels of EVs adoption (endogenous) variable (Refer to table 5 and table 6: encourage factors marked in bold). These three factors are resale value, environmental performance and recharging infrastructure, which can be considered as major enablers for enhancing EV use.

Environment factors corresponds to 0.050 (Table 5) and 0.041 (Table 6) as standardized total effects coefficient value in both encourage EV adoption models, which indicate that people appreciate low carbon emission of EV and this reflects the environmental friendly nature of society. However, increase in EV demand in future will lead to increment in electricity demand, therefore electricity for EVs need to come from renewable energy sources in order to make it a true green alternative to internal combustion vehicles (Degirmenci & Breitner, 2017). According to National statistics (Evans, 2018), 52% of electricity is generated through fossils fuels in UK, with 30.1% share of renewable sources. As, showed from a study in united states that transition to EVs would in turn increase CO2 emissions as half of electricity is generated from coal (Hasan & Dwyer, 2010). Therefore, there is need of improvement in renewable sector share in overall electricity generation. Environmental issues might be viewed as abstract and less instantaneous, and the responses of most people to these aspects may be less crucial than their responses to the standards of society to which they belong, which they consider as better indication of what is acceptable and adequate (Ozaki & Sevastyanova, 2011). This direct towards significant role of society norms and pressure in acceptance of sustainable behaviour. This effect can be seen in our study as people responded environmental factor as the most important factor while buying a car, with 73.3% (Table 1) positive response rate, on the other hand only 6.5% (Table 1) positive response is received where environmental factor is asked as encouragement factor for EV. Other encourage factors which include resale value and recharging infrastructure, their effects on EVs adoption are discussed below in car ownership section 4.3.3.

4.3.3. Car ownership impact on EVs adoption

Car ownership, which is acting as a mediating variable, is positively associated with private car usage frequency, with 0.359 (Table 4) and 0.366 (Table 6) as values for standardized total effect coefficients (effect of public transport use on car ownership),and negatively with public transport, with -0.258 (Table 3) and -0.265 (Table 5) as values for standardized total effect coefficients (effect of public transport use on car ownership),which can be stated as an obvious fact that people owning a car are less likely to use public transport. On the other hand, car ownership is also positively correlated with levels of EVs adoption, with significant values of coefficients of standardized total effects as 0.202 (Table 3), 0.169 (Table 4), 0.219 (Table 5) and 0.179 (Table 6), which are effects of car ownership on levels of EVs adoption, in all four models. Therefore, it can be interpreted that people owning multiple cars represents high economic status and hence they can afford buying an electric vehicle either as an additional vehicle or in replacement of their existing car, and hence are more likely to adopt an electric vehicle in future.

Car ownership has a strong correlation with the recharging infrastructure, with standardized total effects as 0.073 (Table 3), 0.055 (Table 4), 0.079 (Table 5) and 0.060 (Table 6) on car ownership, and resale value, with standardized total effects as 0.046 (Table 3), 0.041 (Table 4), 0.015 (Table 5), 0.030 (Table 6) on car ownership, with the better correlation of former variable rather than the latter. This relationship suggested that due to the lack of recharging stations, there is insecurity while commuting long distance journey thus people will prefer ICE vehicle over EV, and also if they own an EV in near future they will be bound to use it, only for short-range driving purposes. Resale value factor's positive correlation with car ownership indicate that people who already own a car, are supposed to have more knowledge of car market than the rest population. Therefore, resale value factor plays significant role in encouragement behaviour towards EV, as in a situation where an individual want to sell his EV and he will be receiving a satisfactory amount compared to the sum he will receive for selling an ICE vehicle, in this scenario he will be more inclined towards EV adoption. This situation can be implemented through successful market penetration of EVs, as this will lead to an increment in its resale value.

4.3.3. Revealed travel behaviour impact on EVs adoption

Frequency of public transport use causes negative impact on level of EV adoption, both directly and indirectly. As can be seen Table 3 of put off EV adoption model, where -0.043 (direct effect) and -0.052 (indirect effect) add to give -0.095 (total effect). Similarly in Table 5 of encourage EV adoption model, where -0.048 (direct effect) and -0.058 (indirect effect) add to give -0.106 (total effect). This can be interpreted that public transport users might not own a private vehicle, as they have negative correlation with car ownership, with -0.258 (total effect) in Table 3 and -0.265

(total effect) in Table 5, due to perhaps lack of driving experience. Thus, they are not expected to adopt an EV in future, as they do not drive and they will not be willing to switch their current mode of transport. It can be seen from the results that indirect effect of public transport usage on EV adoption level, is contributing as much as its direct effect, therefore by considering standardized direct effect coefficient it can be interpreted that even if a public transport user owns a car, he will not be willing to switch to EVs because he already has options to choose either public transport or his private car as a modal preference for his journey. On the other hand, private car users are more likely to switch to EV in future, as determined by their positive impact on EV attitude, both directly and indirectly, can be seen Table 4 of put off EV adoption model, where 0.114 (direct effect) and 0.061 (indirect effect) add to give 0.175 (total effect). Similarly in Table 6 of encourage EV adoption model, where 0.129 (direct effect) and 0.065 (indirect effect) add to give 0.195 (total effect). Thus, from the above results, when the standardized total effects of public transport user and private car user on level of EV adoption are compared, it is evident that private car users has the most significant positive impact on EVs adoption level and also that if a private car user, have a car ownership, it will increase his likelihood to adopt EV in future. Above mentioned explanations signifies the importance of indirect effect, as only focusing on direct effects can lead to inconsistent conclusions in some scenarios, therefore before making the final interpretation both direct and indirect should be interpreted carefully (Van Acker & Witlox, 2010).

4.3.3. Socio-demographic variables impact on EVs adoption

Among the socio-demographic exogenous variables, education level of respondents turns out to be the most influential factor on their corresponding EV adoption attitude, with standardized total effects as 0.157 (Table 3), 0.162 (Table 4), 0.180 (Table 5) and 0.183 (Table 6) on level of EVs adoption. This indicate that people with superior education background seems to have more knowledge regarding the benefits of adopting an electric vehicle. Therefore government, automobile manufactures, private companies can organize promotional programs, workshop and campaigns, to create awareness among consumers about advantages of EVs, so that after analyzing all the pros and cons they can finally able to make an unbiased decision for an EV. These promotional events can circulate information regarding government's current EVs grants and schemes, recharging infrastructure development, rapid chargers distributions, and finally recent technological advancements in EVs field which will counter the technology unreliability barrier (finding of our study). Education level is positively linked to both public transport (0.079 as total effect in both table 3 & 5) and private car usage (0.093 as total effect in both table 4 & 6), this represents inclusion of different sections of society, i.e., students who are more likely using public transport and employed sector who are commuting their journey to work using either of the transport modes, as many companies has the policies of promoting public transport usage among their employers.

Similarly, home ownership, employment and income level have positive impact on EVs adoption level (refer table 3, 4, 5, 6), as this represent financially wellbeing status of people, thus also indicating towards their affordability of EV. This can also be implied because these factors are also positively associated with car ownership and private car usage, while negatively related to public transport usage. Similar relationship is also observed in case of household size, which represents joint families and hence more demand of car amongst them. Age is associated with negative impact on EVs adoption in all models, with standardized total effects as -0.058 (Table 3), -0.054 (Table 4), -0.064 (Table 5) and -0.060 (Table 6) on levels of EVs adoption, this indicate that senior citizens are less likely to adopt EV as perhaps they are already satisfied with their current mode of transport as much as technology discussed in (Pangbourne, Aditjandra, & Nelson, 2010),whether it will be a private car or public transport. Similarly, gender is also negatively correlated with EVs adoption, with standardized total effects as -0.086 (Table 3), -0.097 (Table 4), -0.102 (Table 5) and -0.114 (Table 6) on levels of EVs adoption, as in the dataset male are represented as 0 and female as 1, therefore it can implied that females are less inclined towards EVs adoption. This behaviour can be implied due to their lack in car ownership status and driving experience, which can be validated as gender is also negatively related with car ownership variable.

5. Conclusion and recommendations

This study applies an SEM in a public attitudes towards EVs dataset to understand the relationships between levels of EV adoption, car ownership and travel behaviour. We found that battery (range confidence), recharging infrastructure and technology (unreliability) can be considered as major indicators in influencing EV adoption. We also found that resale value, environmental performance and recharging infrastructure are major enablers of EV adoption. This study has a few limitations: firstly, it only focuses on attitudinal behaviour of people and did not take into account non-attitudinal variable which might impact government policy interventions and effect of oil price fluctuation, these parameters falls outside the scope of this study. Secondly, the interviews were conducted in United Kingdom (UK), therefore course of action can be different in other countries, due to demographic and cultural differences, and also due to the difference in levels of EVs exposure in various countries. Thirdly, majority of participants do not actually own an EV: there are only four EV owners out of 1850 respondents, therefore their attitudes and intentions might change after having a driving experience in EV. Further research is recommended to repeat this interview process with much more EV users in sample, so that these findings can be compared with this study to obtain better results. However, findings of our study is consistent with other EVs studies, which is pointing out range confidence and recharging infrastructure as the major indicator for EVs adoption (Egbue & Long, 2012, Larson et al., 2014) and Wang et al., 2017), and also environmental performance is one of the major enablers for enhancing EVs use (Degirmenci & Breitner, 2017). An important and unique findings of this study are, consideration of technological unreliability (put off factor) as one of the major indicator, and identification of resale value as the most significant enabling factor for EVs adoption.

The study shows that in terms of standardized coefficients, socio-demographic characteristics and their travel behaviour are main contributors towards change in EVs attitude and consequently EV adoption. This will be crucially needed to realistically address the government agenda of transitioning into a full EV market domination. As government has a crucial role to play in sponsoring EVs market and technological research, disseminating objective information, and educating consumers (Larson et al., 2014). Pointing out education importance as also one of the main findings in our models, we would like to agree to Egbue & Long, (2012) study which has stated that, EVs grants and incentives such as tax credits and fuel taxes may have little effect on market penetration, if consumers have low confidence in EV technology. Therefore, consumer awareness through education, i.e. experience and exposure to EVs, is the most crucial factor for policy which intend to increase uptake of these vehicles.

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Appendix A.

Interview questions:

Which of these statements best describes your current attitude towards buying an electric car or van?
- I already own an electric car or van.
- I am thinking about buying an electric car or van quite soon.
- I am thinking about buying an electric car or van, but I haven't thought about when I will buy it.
- I have thought about buying an electric car or van, but I have decided not to at this stage.
- I haven't really thought about buying an electric car or van.
- I have never heard of electric cars or vans.
- I do not drive / do not need a car.
- Do not know (spontaneous only)

If you were to buy a car or van in the next 12 months, what, if anything, would put you off buying an electric car or van?
- Limited choice (not many vehicles to choose from)
- Lack of knowledge
- Cost
- Battery: distance travelled on charge
- Recharging
- Resale value / residual value
- Safety features / record
- The vehicle: performance (e.g. speed / handling), size / practicality, looks
- Technology: does not work / not proven
- Nothing
- Other (please specify)
- Do not know
- Refusal

Thinking about the next time you buy a new car or van, whether brand new or second-hand, what would encourage you to buy an electric car or van?

- Cost
- Battery: distance travelled on charge
- Convenience of recharging
- Resale value/residual value
- Safety features/record
- Vehicle size, performance or aesthetics
- If there was more choice available
- Technology: reliable/proven
- Environmentally friendly/ produces lower CO2 emissions
- Nothing
- Other (please specify)
- Do not know (spontaneous only)
- Refusal (spontaneous only)