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a literature review

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Consumer preferences for electric vehicles: a literature review

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ABSTRACT

Widespread adoption of electric vehicles (EVs) may contribute to the alleviation of problems such as environmental pollution, global warming and oil dependency. However, the current market penetration of EV is relatively low in spite of many governments implementing strong promotion policies. This paper presents a comprehensive review of studies on consumer preferences for EV, aiming to better inform policy-makers and give direction to further research. First, we compare the economic and psychological approach towards this topic, followed by a conceptual framework of EV preferences which is then implemented to organise our review. We also briefly review the modelling techniques applied in the selected studies. Estimates of consumer preferences for financial, technical, infrastructure and policy attributes are then reviewed. A categorisation of influential factors for consumer preferences into groups such as socio-economic variables, psychological factors, mobility condition, social influence, etc. is then made and their effects are elaborated. Finally, we discuss a research agenda to improve EV consumer preference studies and give recommendations for further research.

Abbreviations: AFV: alternative fuel vehicle; BEV: battery electric vehicle; CVs: conventional vehicles; EVs: electric vehicles; FCV: fuel cell vehicle; HCM: hybrid choice model; HEV: hybrid electric vehicle (non plug-in); HOV: high occupancy vehicle; MNL: MultiNomial logit; MXL: MiXed logit model; PHEV: plug-in hybrid electric vehicle; RP: revealed preference; SP: stated preference.

1. Introduction

Many governments have initiated and implemented policies to stimulate and encourage electric vehicle (EV) production and adoption (Sierzchula, Bakker, Maat, & Van Wee, 2014). The expectation is that better knowledge of consumer preferences for EV can make these policies more effective and efficient. Many empirical studies on consumer preferences for EV have been published over the last decades, and a comprehensive literature review would be helpful to synthesise the findings and facilitate a more well-rounded understanding of this topic. Rezvani, Jansson, and Bodin (2015) give an overview of EV adoption

studies; however, they only focus on individual-specific psychological factors which influence people's intention for EV adoption and only select some representative studies. Our review complements it in the following ways: first, we review a wider range of influential factors in EV adoption other than psychological constructs only; second, we present a comprehensive picture of current research by collecting all the available academic EV preference studies.

This literature review aims to answer the following questions: (1) How are EV preference studies conducted (methodology, modelling techniques and experiment design)? (2) What attributes do consumers prefer when they choose among specific vehicles? (3) To what extent do these preferences show heterogeneity? What factors may account for heterogeneity? (4) What research gaps can be derived from the review and what recommendations can we give for future research?

To gather research articles for the study, we used several search engines and databases as a start: Google Scholar, Web of knowledge, ScienceDirect, Scopus and JSTOR.[1] The keywords used in searching were *electric vehicles* combined with *consumer preferences* or *choice model*.[2] Many of these articles contain a brief review of existing research, which enabled backward snowballing. The articles used in this review were selected based on their relevance to the research questions. We only include studies after 2005 because they cover all the attributes used in pre-2005 research and use more advanced modelling techniques.

EVs come in different types and can be categorised into hybrid electric vehicles (HEVs) and plug-ins: HEVs have a battery which only provides an extra boost of power in addition to an internal combustion engine and increases fuel efficiency due to recharging while braking; while plug-ins can be powered solely by battery and have to be charged by plugging into a power outlet. Plug-ins can be further divided into plug-in hybrids (PHEVs, which are powered by both a battery and/or engine) or full battery electric vehicles (BEVs). Our review focuses only on BEV and PHEV, since – unlike HEVs – they require behavioural changes as they require charging. However, studies on HEV were also included when they involve relevant factors which are not yet covered in BEV and PHEV preference studies.

This paper is organised as follows: Section 2 presents a conceptual framework for the review after comparing different methodological approaches and then discusses the modelling techniques of EV preference studies. Section 3 describes the importance of various attributes of EV in consumers' choices. Section 4 discusses the factors which are influential in EV preferences. The final section presents the main findings, an integrative discussion and a research agenda.

2. Conceptual framework and methodologies in EV preferences studies

2.1. Methodological approaches and conceptual framework of EV preferences studies

In this section, we propose a conceptual framework for EV preferences based on which we organise our review. Before presenting the framework, we first briefly introduce its background.

Based on the differences in focusing factors, theories and models, studies concerning EV adoption can be roughly divided into two categories: economic and psychological.

The most widely applied methodology among economic studies is discrete choice analysis in which EV adoption is described as a choice among a group of vehicle alternatives described by their characteristics or "attributes". Consumers make decisions by making trade-offs between attributes. Economic studies focus on estimating the taste parameters for attributes which denote their weights in the decision. Psychological studies focus on the motivation and process of decision-making by examining the influence of a wide range of individual-specific psychological constructs (attitudes, emotion, etc.) and perceptions of EV on intentions for EV adoption. Their strength lies in uncovering both the direct and indirect relationships between these constructs and the intention. In contrast to economic studies, these studies generally ignore other vehicle options (conventional vehicles (CVs) such as gasoline and diesel vehicles) and do not specify or systematically vary the EV attributes. Consequently, psychological studies only provide limited (if any) insight into how changes in the attributes of EV can lead to a shift in preferences for EV. Moreover, discrete choice analysis also allows the incorporation of psychological constructs, which enables a more comprehensive conceptual framework than that of psychological studies.

This review utilises the framework applied in economic studies for two reasons: first, many governments or car manufacturers aim to increase EV adoption by improving EV attributes or the supporting service system (e.g. charging infrastructure etc.), and discrete choice analysis – used by economic studies – is more suitable for evaluating the potential effectiveness of these policies or strategies. The second reason is that it can relatively easily incorporate factors and theories from psychological studies.

Figure 1 presents our framework. Vehicle adoption is essentially choosing a vehicle from the given set of alternatives. Although there are other possible decision rules, decision-
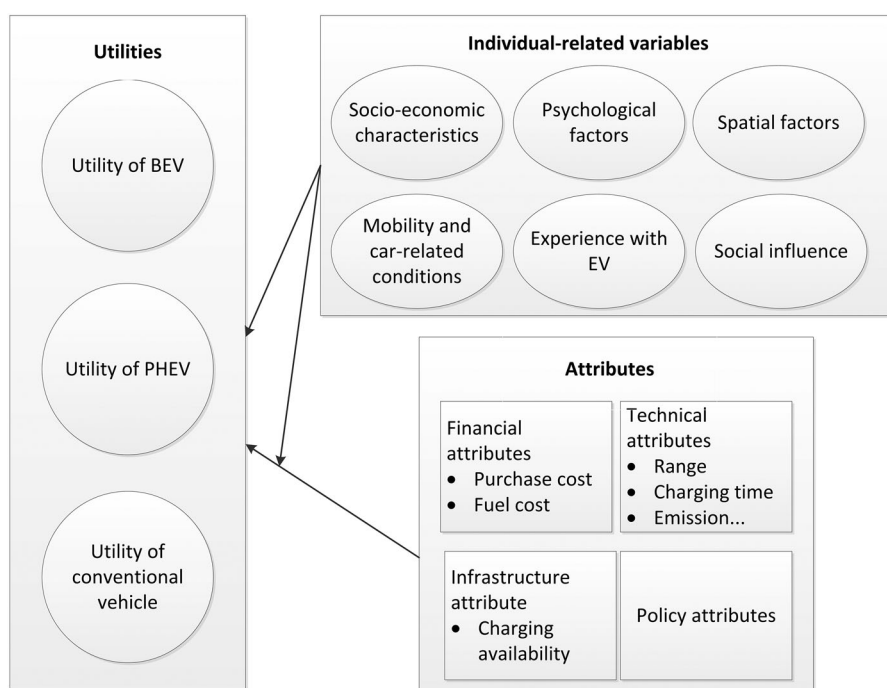

Figure 1. Conceptual framework of EV preference.

makers are most commonly assumed to choose the alternative that maximises their utility. The utility of each alternative is generally assumed to be a linear combination of all the attributes of the alternative multiplied by a taste parameter that denotes the weight of the attribute for an individual. Choice data are used to calibrate discrete choice models by estimating the value of taste parameters in utility functions. To include preference heterogeneity (the value of taste parameters varies in the population) many choice studies include individual-related variables to capture heterogeneity. These variables either directly influence utilities or moderate the relationship between attributes and utilities.

2.2. Review of modelling techniques

We mainly focus on studies applying the economic approach, while other studies are also mentioned if their findings highlight additional factors and relationships. Table 1 gives an overview of the studies reviewed.

All studies are based on SP (stated preference) data due to the lack of a large-scale presence of EVs in the market. SP data is collected by choice experiments in which respondents making one choice from given set of alternatives. Attribute values vary between alternatives and can be hypothetical.

As for data analysis, the mainstream choice model has evolved: first, most studies only estimated the most basic MultiNomial logit (MNL) model (McFadden, 1974). However, MNL assumes independence from irrelevant alternatives (IIAs), which does not hold in most cases. Thus, some studies used nested logit models to relax the restriction of IIA (Train, 2003). Nested logit models account for the correlation between alternatives by clustering alternatives into several "nests": alternatives in the same nest are more similar and compete more with each other than with those belonging to different nests.

Taste parameters in both MNL and nested logit model are fixed constants, implying that preferences do not vary across consumers, which is often unrealistic. In order to accommodate differences in preferences, the mixed logit model became common practice from about 2010: by assuming taste parameters to be randomly distributed, it captures preference heterogeneity albeit without offering explanations (McFadden & Train, 2000). Three methods are typically used to identify the source of heterogeneity:

- Traditional segmentation: interaction items between measured individual-specific variables and attributes (or alternative specific constant (ASC)) are added to the utility function to test for its statistical significance. Usually, this is conducted in an explorative fashion: it has very little theoretical basis and conclusions are drawn solely based on *p*-values. The significance of variables is influenced by model specification since a variable may lose significance after controlling for its correlations with added variables.
- Identifying influential latent variables: the hybrid choice model (HCM) is the current state-of-the-art method for accounting for heterogeneity (Ben-Akiva et al., 2002). It incorporates latent (usually psychological) variables which are measured by several indicators and assumed to be influenced by exogenous (e.g. socio-economic) variables. However, applying its insights to policy-making is rather difficult (Chorus & Kroesen, 2014).
- Categorising consumers based on different preferences by estimating a latent class model (Boxall & Adamowicz, 2002), assuming that people can be classified into several classes:

Table 1. Overview of studies.

Author(s) (year)	Country	Time of data collection	Number of respondents	Number of choice tasks for each respondent	New vehicle alternatives included in given choice set[a]	Estimation model
Horne, Jaccard, and Tiedemann (2005)	Canada	2002–2003	866	4	NGV (natural gas vehicle), HEV, FCV (fuel cell vehicle)	MNL (MultiNomial logit model)
Potoglou and Kanaroglou (2007)	Canada	2005	482	8	AFV (general), HEV	Nested logit model
Mau, Eyzaguirre, Jaccard, Collins-Dodd, and Tiedemann (2008)	Canada	2002	916HEV 1019FCV	18	HEV, FCV	MNL
Hidrue, Parsons, Kempton, and Gardner (2011)	USA	2009	3029	2	BEV	Latent class model
Mabit and Fosgerau (2011)	Denmark	2007	2146	12	AFVs including BEV, HEV	MXL (MiXed logit model)
Musti and Kockelman (2011)	USA	2009	645	4	HEV, PHEV	MNL
Qian and Soopramanien (2011)	China	2009	527	8	BEV, HEV	Nested logit model
Achtnicht, Bühler, and Hermeling (2012)	Germany	2007–2008	598	6	AFVs including BEV, HEV	MNL
Daziano (2012)	Canada	Same as Horne et al. (2005)			NGV, HEV, FCV	HCM (hybrid choice model)
Hess, Fowler, and Adler (2012)	USA	2008	944	8	AFVs including BEV	Cross-nested logit model
Molin, Van Stralen, and Van Wee (2012)	Netherlands	2011	247	8 or 9	BEV	MXL
Shin, Hong, Jeong, and Lee (2012)	South Korea	2009	250	4	BEV, HEV	Multiple discrete-continuous extreme value choice model
Ziegler (2012)	Germany	Same as Achtnicht et al. (2012)			AFVs including BEV, HEV	Probit model
Chorus, Koetse, and Hoen (2013)	Netherlands	2011	616	8	AFVs including BEV, PHEV	Regret model
Daziano and Achtnicht (2013)	Germany	Same as Achtnicht et al. (2012)			AFVs including BEV, HEV	Probit model
Daziano and Bolduc (2013)	Canada	Same as Horne et al. (2005)			NGV, HEV, FCV	Bayesian HCM
Hackbarth and Madlener (2013)	Germany	2011	711	15	AFVs including BEV, PHEV	MXL
Jensen, Cherchi, and Mabit (2013)	Denmark	2012	369	8	BEV	HCM
Rasouli and Timmermans (2013)	Netherlands	2012	726	16	BEV	MXL
Bockarjova, Knockaert, Rietveld, and Steg (2014)	Netherlands	2012	2977	6	BEV, HEV	Latent class model
Glerum, Stankovikj, and Bierlaire (2014)	Switzerland	2011	593	5	BEV	HCM
Hoen and Koetse (2014)	Netherlands	2011	1903	8	AFVs including BEV, PHEV	MXL
Kim, Rasouli, and Timmermans (2014)	Netherlands	Same as Rasouli and Timmermans (2013)			BEV	HCM
Tanaka, Ida, Murakami, and Friedman (2014)	USA/Japan	2012	4202/4000	8	BEV, PHEV	MXL
Helveston et al. (2015)	USA/China	2012–2013	572/384	15	BEV, PHEV, HEV	MXL
Valeri and Danielis (2015)	Italy	2013	121	12	AFVs including BEV	MXL

Notes: AFV (general): AFV included as a single alternative without specifying fuel type.
AFVs including … : Other AFVs (LPG, biofuel, flexifuel …) are also included as alternatives.
[a]This column lists the included vehicle alternatives apart from conventional ones (gasoline, diesel).

each class has a different preference profile, and class membership depends on individual characteristics. It is easy to use and interpret, but as with the HCM it is difficult to apply in policy-making because it is not straightforward to locate target groups.

These more advanced models generally have a significantly higher model fit than the basic MNL model. It is however unknown how they compare with each other regarding model fit since none of the studies estimated multiple advanced models. Moreover, these models differ vastly regarding specific model structure and the number of parameters, which makes a comparison of model fit far from straightforward. Overfitting is also worth noting: choice studies rarely check the prediction reliability of their models and try to achieve higher model fit by using an excessive number of parameters, which may lead to the potential problem of overfitting.

3. A review of preferences for EV attributes

EV preference studies generally include the *financial, technical, infrastructure* and *policy attributes* for vehicle alternatives. In addition they include ASC in the utility function, capturing the joint effect of all the attributes of an alternative which are not included in the choice experiment. The ASC for EV is usually interpreted as a basic preference for EV compared to conventional cars when everything else is equal. Since different studies usually include different attributes, by definition the ASCs in these models cover different factors and cannot be directly compared.

This section presents an overview of the findings on the preferences for different attributes of EV. An overview of attributes (without policy attributes) can be found in Table 2. For each attribute, we first discuss its operationalisation to see how it is defined and measured in the choice experiments, and then present its parameter significance. We also elaborate whether preferences vary among samples and provide some explanation for preference heterogeneity if applicable. Because there are many sporadic findings regarding the relationship between individual-related variables and the taste parameters of attributes, we only discuss those which are either reasonable/counter-intuitive/inspiring or repeatedly confirmed.

3.1. Financial attributes

Financial attributes refer to various types of monetary costs of vehicle purchase and use:

Purchase price is included in all the reviewed studies. Many studies used pivoted design for this attribute: price levels are customised and pivoted around the price of a reference vehicle stated by each respondent. Purchase price was found to have a negative and highly significant influence on the EV utility in all studies. In most of the studies this is explored as a linear relationship, with rare exceptions, for example Ziegler (2012) who attempted to capture the non-linear effect by using logarithms of the price.

Price preferences also vary among populations. Rasouli and Timmermans (2013) found that heterogeneity is particularly high when the price of EV is much higher than CV. Several studies discovered an income effect, namely that people with high incomes are less price-sensitive than others (Achtnicht et al., 2012; Hackbarth & Madlener, 2013; Hess et al., 2012; Mabit & Fosgerau, 2011; Molin et al., 2012; Potoglou & Kanaroglou, 2007; Valeri & Danielis,

Table 2. Overview of financial, technical and infrastructure attributes.

Attributes	Operationalisation	References[a]
Purchase price	Price	All studies in Table 1
Operation cost	Price per 100 km Fuel efficiency	All studies in Table 1
Driving range	Range after full charge	Chorus et al. (2013); Hackbarth and Madlener (2013); Helveston et al. (2015); Hidrue et al. (2011); Hoen and Koetse (2014); Jensen et al. (2013); Mabit and Fosgerau (2011); Mau et al. (2008); Molin et al. (2012); Qian and Soopramanien (2011); Tanaka et al. (2014); Rasouli and Timmermans (2013); Valeri and Danielis (2015) *Insignificant*: Hess et al. (2012)
	Maximum/minimum range	Bockarjova et al. (2014)
	All-electric range (PHEV)	Helveston et al. (2015)
Charging time	Time for a full charge	Bockarjova et al. (2014); Chorus et al. (2013); Hackbarth and Madlener (2013); Hidrue et al. (2011); Hoen and Koetse (2014); Rasouli and Timmermans (2013)
Engine power	Horsepower	Achtnicht et al. (2012); Horne et al. (2005)
Acceleration time	Time from 0–100 km/h	Helveston et al. (2015); Hess et al. (2012); Hidrue et al. (2011); Potoglou and Kanaroglou (2007); Valeri and Danielis (2015) *Insignificant*: Mabit and Fosgerau (2011)
Maximum speed	Speed (km/h)	Rasouli and Timmermans (2013)
CO_2 emission	Emission per km	Achtnicht et al. (2012); Jensen et al. (2013)
	Percentage relative to reference vehicle	Hackbarth and Madlener (2013); Hidrue et al. (2011); Potoglou and Kanaroglou (2007); Tanaka et al. (2014)
Brand	Country origin of brand	Helveston et al. (2015)
Brand diversity	Number of brands available	Chorus et al. (2013); Hoen and Koetse (2014)
Warranty	Period/range covered by warranty	Mau et al. (2008)
Charging availability	Distance from home to charging station	Rasouli and Timmermans (2013) *Insignificant*: Valeri and Danielis (2015)
	Detour time than to gas station	Bockarjova et al. (2014); Chorus et al. (2013); Hoen and Koetse (2014)
	Percentage of the number of gas stations	Achtnicht et al. (2012); Hackbarth and Madlener (2013); Horne et al. (2005); Mau et al. (2008); Potoglou and Kanaroglou (2007); Qian and Soopramanien (2011); Shin et al. (2012); Tanaka et al. (2014)
	Presence in different areas	Molin et al. (2012); Jensen et al. (2013) *Insignificant*: Hess et al. (2012)

[a]If not marked, all references listed find the attribute significant. As for studies which use the same dataset, only the earliest published study is listed here.

2015), while Jensen et al. (2013) found this effect to be insignificant. Preferred car size also plays a role in price sensitivity: Jensen et al. (2013) concluded that buyers of smaller cars have a higher marginal utility of price. People who choose used cars also find price to be more important (Hoen & Koetse, 2014; Jensen et al., 2013). Moreover, individuals who are more interested in the practical aspects of the car as opposed to design are less affected by price (Glerum et al., 2014).

Operation cost also appears in every study albeit in slightly different forms. Most studies use energy cost as the attribute: either cost per (100) km or both fuel efficiency and fuel price (Musti & Kockelman, 2011). Some studies also include regular maintenance costs (Hess et al., 2012) or combine it with energy costs as a combined operation cost attribute (Mabit & Fosgerau, 2011). These all negatively affect the decision to purchase a car, which gives EV an edge over CV since EV generally has lower energy costs (Mock & Yang, 2014). Jensen et al. (2013) found that the marginal utility of fuel cost for EV is much higher than for CV.

Again, people with higher incomes place lower importance on fuel cost (Helveston et al., 2015; Valeri & Danielis, 2015). However, Chinese respondents with higher income

are more sensitive to high fuel costs (Helveston et al., 2015). This effect implies that in China the attraction of EV is reinforced since rich people who can afford EV also value the cost savings it brings in its daily operation.

Battery lease cost is only included in Glerum et al. (2014), which considers a business model different from one-time purchase. Similar to other costs, it has a negative impact on the purchase decision, as expected. In addition, people who have a more "pro-leasing" attitude are less sensitive towards lease cost. Valeri and Danielis (2015) also included an alternative with the option of battery lease but did not disentangle its effect from the impact of brands.

3.2. Technical attributes

Technical attributes describe the technical characteristics of the vehicle itself:

A relatively short *driving range* is considered to be one of the biggest barriers to the widespread adoption of EV. The most common operationalisation is driving range with a full battery. An exception is Bockarjova et al. (2014), which included both range under normal and unfavourable circumstances. Range is found to have a positive and statistically significant effect on EV adoption decisions in the vast majority of studies. However, Hess et al. (2012) found this effect to be insignificant, which may be explained by the limited range used in their experiment (30–60 miles). Jensen et al. (2013) found that the marginal utility for driving range is much higher for an EV than for a CV, which is probably due to the large difference in range between these two car types. Following a meta-analysis, Dimitropoulos, Rietveld, and Van Ommeren (2013) proposed that preference for range may be sensitive to charging station density and charging time. In the case of PHEV, a longer all-electric range (the distance solely battery-powered) also increases the likelihood of purchase (Helveston et al., 2015).

The heterogeneity in the preference is higher when the range is significantly lower than the range of an average CV (∼100 km) (Rasouli & Timmermans, 2013), which indicates a polarised preference towards the range of most current BEVs. People with a lower annual mileage have a lower preference for driving range (Hoen & Koetse, 2014). Households with multiple cars are less concerned about a relatively low EV range (Jensen et al., 2013), since they have a CV available for long distance trips. Franke, Neumann, Bühler, Cocron, and Krems (2012) claimed that certain personality traits and coping skills for stress can relieve worries about the EV range. Direct experience with EV is also expected to be helpful in reducing "range anxiety". Bunce, Harris, and Burgess (2014) and Franke and Krems (2013) found that throughout a trial period drivers became more relaxed. However, Jensen et al. (2013) found people to value the EV driving range almost twice as highly once they had driven an EV for three months.

Recharging time is found to be significant in all the studies that included it. However, apart from Bockarjova et al. (2014), none of the studies distinguished between slow and fast charging. Recharging time depends on the power of the charging post and the battery capacity. For everyday purpose, EV uses *slow charging* at home or at work which takes around 6–8 hours for a full charge. As for recharging during long trips, fast chargers can fill the battery up to 80% within 15–30 minutes. In other words, "charging time" varies greatly depending on the conditions.

Performance is usually represented by engine power, acceleration time or maximum speed. Consumers are generally found to prefer better performance. However, acceleration time is found to be insignificant in Mabit and Fosgerau (2011) since heterogeneous preferences among the population may cancel each other out: males have a significant preference for faster acceleration while females prefer slower acceleration (Mabit & Fosgerau, 2011; Potoglou & Kanaroglou, 2007; Valeri & Danielis, 2015). Potoglou and Kanaroglou (2007) also found that single people value shorter acceleration time more.

Although emissions of BEV while driving are absent, many studies still set different levels of *CO$_2$ emission* for EV in the choice experiment, representing the emissions of electricity generation. Choice experiments either directly use absolute CO_2 emission per kilometre or the percentage relative to a gasoline vehicle. Hackbarth and Madlener (2013) found that for environmentally friendly people the same amount of emission brings higher disutility.

Brand and diversity: Valeri and Danielis (2015) included the car model in the label in the choice experiment; however, the effect was not separated from fuel type. Helveston et al. (2015) found that people prefer brands from certain countries and the preference order differs between countries. Chorus et al. (2013) and Hoen and Koetse (2014) found that having more EV models available on the market increases the probability of choosing an EV. It can be seen as an indicator of EV market maturity and thus influence people's perception of uncertainty. This may account for the low sales of EV as at present there only a few brands with EVs for sale, and some potential EV buyers probably do not like the specific brands or prefer more options to choose from.

Warranty is found to affect EV adoption positively (Mau et al., 2008). Jensen et al. (2013) found the influence of battery life to increase after respondents participated in a three-month trial period of EV but both effects are non-significant. This issue is expected to be relevant because there are a lot of uncertainties regarding battery life and consumers may prefer more certainty for these aspects. Based on the existing results the significance of a warranty's effect remains unclear.

3.3. Infrastructure attributes

Infrastructure attributes focus on the availability of the charging infrastructure. There is not yet consensus regarding its operationalisation: some studies show the density of charging stations relative to gas station; Rasouli and Timmermans (2013) use the distance from home to the closest charging station, while others present the presence of a charging station in different areas: at home, at work or in shopping malls, etc.

In most studies it has a significantly positive effect, possibly because more charging facilities save time and search cost for users as well as relieving their range anxiety as well. Achtnicht et al. (2012) found the effect to be non-linear with a diminishing marginal utility. Charging posts in different activity locations are preferred by certain groups: for example, Jensen et al. (2013) found that long distance commuters value chargers in work places significantly more than others, and prefer a higher density of charging stations (Potoglou & Kanaroglou, 2007).

The reviewed studies do not however differentiate slow charging posts from fast charging stations, while– as explained above – these two serve different purposes. Public slow charging posts are mainly situated in workplaces or shopping malls where parking is for

longer periods, while fast charging stations are mostly located on highways (also in cities but only for emergency) to support longer EV trips. Most importantly, unlike CV which requires regular visits to gas stations for refuelling, EV allows users to rely on home charging as long as one's daily distance is within the EV's range, which applies to most people (Tamor, Moraal, Reprogle, & Milačić, 2015). Bunce et al. (2014) reported that after a trial period, users preferred recharging at home to refuelling at petrol stations due to its convenience. In contrast, since EVs mostly rely on slow charging, it is almost impossible to use an EV regularly if there is no charging facility at home or work. Whether respondents were fully aware of this was not clear.

3.4. Policy attributes

Policy attributes include different policy instruments for promoting EV adoption. If the preference parameter for a certain policy attribute in the final choice model is significant, then the policy can be regarded as potentially effective. Five policies were tested in the reviewed studies. Table 3 gives an overview of their findings.

Regarding one-time price reducing policies, *reducing purchase tax* is significant in all cases while *reducing purchase price* is only significant 2 out of 4 times. The difference can be most clearly seen in contrast to Hess et al. (2012): a $1000 tax reduction is significantly positive while a $1000 price reduction is not significant. This can possibly be due to the higher symbolic value attached to a higher priced car. Gallagher and Muehlegger (2011) also found that the type of tax incentive offered is as important as the generosity of the incentive.

As for usage cost reduction policies, *annual tax reduction* seems to be the only significant policy, while *free parking* and *toll reduction* are not significant in any of the studies that explored their effects. The effectiveness of different types of tax reduction reflects the difference in perceptions people have towards taxes versus other expenses.

As for the only non-financial policy tested, the effectiveness of *giving EV access to HOV lanes* remains ambiguous. There may be several reasons for the contradictory findings and lack of significance of potential non-financial policy instruments. First, the location of the

Table 3. Overview of policy attributes.

Policy	Studies which find it effective	Studies which find it ineffective
Pricing policies: One-time reduction		
Reduce/exemption of purchase tax	Hess et al. (2012); Potoglou and Kanaroglou (2007)	
Reduce purchase price	Glerum et al. (2014); Mau et al. (2008)	Hess et al. (2012); Qian and Soopramanien (2011)
Pricing policies: usage cost reduction		
Reduce/exemption of road tax	Chorus et al. (2013); Hackbarth and Madlener (2013); Hoen and Koetse (2014)	
Free parking		Chorus et al. (2013); Hess et al. (2012); Hoen and Koetse (2014); Potoglou and Kanaroglou (2007); Qian and Soopramanien (2011)
Reduce toll		Hess et al. (2012)
Land-use policy		
Access to HOV (high occupancy vehicle)/express/priority/bus lane	Hackbarth and Madlener (2013); Horne et al. (2005)	Chorus et al. (2013); Hess et al. (2012); Hoen and Koetse (2014); Potoglou and Kanaroglou (2007); Qian and Soopramanien (2011)

data collection may play a role, people living in cities or regions without serious traffic congestion do not value access to high occupancy vehicle (HOV) lanes much if at all; in addition, good availability of parking spaces and cheap or free parking are likely to lead to indifference towards dedicated and free parking space (Potoglou & Kanaroglou, 2007). Second, people living in places where there are no HOV lanes (Potoglou & Kanaroglou, 2007; Qian & Soopramanien, 2011) may have difficulty perceiving its benefits. Third, the polarised preferences of different groups could lead to an insignificant parameter when considering the entire sample. EV policy incentives which aim to encourage the substitution of CV by EV could have the unintended rebound effect that households increase the number of cars. Holtsmark and Skonhoft (2014) warned about this phenomenon in Norway's case. De Haan, Peters, and Scholz (2007) did not find this effect for HEV.

3.5. Dynamic preference

Choice studies assume that preferences are stable; however, for EV preferences this is untrue for two reasons: first, EV only became available recently and different groups of people will adopt EV successively depending on their acceptance of innovation. People who enter the market at a different point in time are expected to have different preference profiles, therefore the preferences of consumers may vary over time (Rogers, 2003). Second, since EV is still relatively new and unfamiliar to most people and is continuing to develop, people's preferences are expected to evolve along with technological progress, familiarity with EV, market penetration, social influence, etc. If preferences indeed change significantly, the results of EV preference studies that assume static preference are only valid for a limited period of time.

Several studies stressed the importance of dynamics and each focused on one preference-changing factor: Maness and Cirillo (2011) assume dynamic preference due to *technological advancement* by setting different attribute levels for five consecutive years, forming a "pseudo longitudinal" dataset. Motivated by the innovation adoption theory of Rogers (2003), Bockarjova et al. (2014) assigned people into five categories according to their *expected market entry time* and they are found to have different preference profiles. Mau et al. (2008) concluded that preference dynamics can also be caused by changes in the *EV market share*. Rasouli and Timmermans (2013) and Kim et al. (2014) found that *social influence* (EV adoption rate in an individual's social network) also changes people's preference for EV, although the effect is minor. However, these studies only explored one factor separately and did not investigate the combined effect of several possible sources of dynamics.

3.6. Conclusion

Financial, technical and infrastructure attributes are found to have a significant impact on EV choice and this is supported by the vast majority of studies in which they are included. As for policy incentives, tax reduction policies are effective while the effect of other policies (pricing and other) remains controversial. There is preference variance regarding many attributes and several individual-related characteristics have been identified which could account for this.

4. Factors accounting for heterogeneous EV preferences

In this section, we focus on individual-related variables which are found to have an impact on the general preference for BEV and PHEV and attempt to explain part of the taste heterogeneity. Table 4 presents an overview of the main factors explored in previous studies and related findings. One point worth noticing is that almost all individual-related variables are found to be insignificant in at least some studies and excluded in the final model; therefore, we only list cases in which they are found to be significant.

4.1. Socio-economic and demographic characteristics

Socio-economic and demographic characteristics are the categories of individual-related variables most often included in choice studies; however, findings on their effect on EV preference are divergent. For all important socio-economic and demographic variables including gender, age, income, education level and household composition, it is so far unclear whether their effects are positive, negative or significant at all, since there is supporting evidence for all claims (see Table 3). The value and even the direction of their impacts are also sensitive to modelling choices: for example, in Rasouli and Timmermans (2013), the direction of the impact of the gender variable is different in two models based on the same dataset.

4.2. Factors from psychological theories

Psychological theories use a different set of factors to explain behaviour including perceptions, attitudes, norms, etc. Huijts, Molin, and Steg (2012) provided a framework which integrates most of the main psychological theories and factors relevant for sustainable technology acceptance/adoption. Choice studies also attempt to incorporate some of these constructs for a more comprehensive model with higher explanatory power.

Since EV adoption is considered to be motivated by environmental concerns, a personal norm in environmentally friendly behaviour is most often included and found to be positively related to a preference for EV. It is worth noting that its measurement differs among choice studies: most use indicators including environmental concerns and environmentally friendly behaviour, Daziano and Bolduc (2013) measure respondents' awareness of transport problems and support for transport policies. Kim et al. (2014) are the only ones who measure the specific perception of EV as an environmentally friendly vehicle.

As for perception variables, they can be useful to cover the aspects which are not included as attributes in the choice experiment (Petschnig, Heidenreich, & Spieth, 2014). Kim et al. (2014) found that concern for value, battery and technological risks all contribute negatively to the probability of choosing an EV.

EV adoption is sometimes framed as an innovation adoption behaviour due to the novelty of modern EV. The theory of innovation diffusion (Rogers, 2003) suggested that innovativeness of an individual has a positive effect on EV adoption, which was confirmed by a few choice studies. Various psychological studies also concluded that uncertainty for technical progress has a negative impact on the intention to adopt an EV since EV is either

Table 4. Individual-specific variables influential for EV preference.

Factors	Specific variables	Studies which find it has significant positive effect	Studies which find it has significant negative effect
Socio-economic and demographic variables			
Gender	Male	Kim et al. (2014); Rasouli and Timmermans (2013)	Jensen et al. (2013); Qian and Soopramanien (2011); Rasouli and Timmermans (2013)
Age		*PHEV*: Musti and Kockelman (2011)	Achtnicht et al. (2012); Hackbarth and Madlener (2013); Hidrue et al. (2011); Qian and Soopramanien (2011); Ziegler (2012)
		Non-monotonous: Qian and Soopramanien (2013)	
Income		Qian and Soopramanien (2011); Rasouli and Timmermans (2013); *PHEV*: Musti and Kockelman (2011)	Helveston et al. (2015) (US) *PHEV*: Helveston et al. (2015) (US)
Education level		Hidrue et al. (2011); Kim et al. (2014) *PHEV*: Hackbarth and Madlener (2013)	
		Non-monotonous: Rasouli and Timmermans (2013)	
Household composition	Household size	Qian and Soopramanien (2011)	
	Number of kids	Kim et al. (2014); Rasouli and Timmermans (2013)	Qian and Soopramanien (2011)
	Number of drivers in household		Qian and Soopramanien (2011)
Psychological factors			
Pro-environmental attitude		Achtnicht et al. (2012); Daziano and Bolduc (2013); Hackbarth and Madlener (2013); Hidrue et al. (2011); Jensen et al. (2013); Kim et al. (2014); Ziegler (2012)	
		PHEV: Hackbarth and Madlener (2013)	
Concern for battery			Perception of high expense
			Concern for technical risk
Innovativeness		Bockarjova et al. (2014); Hidrue et al. (2011); Kim et al. (2014)	
Car as a status symbol		Helveston et al. (2015) (US)	Helveston et al. (2015) (China)
Mobility and car-related condition			
Current car Condition	Car owner	Qian and Soopramanien (2011)	
	Second-hand car	Jensen et al. (2013)	
	Small or mini	Jensen et al. (2013)	
	Number of vehicles	Helveston et al. (2015) (Only in China); Jensen et al. (2013); Qian and Soopramanien (2011); Ziegler (2012)	*PHEV*: Musti and Kockelman (2011)
Expected car condition	Small or mini	Hackbarth and Madlener (2013); Hidrue et al. (2011)	
	Horsepower		Ziegler (2012)
	Driving range	Ziegler (2012)	

Current mobility habit	Percentage of urban trips	Hackbarth and Madlener (2013)	
	Annual mileage	Ziegler (2012) (expected mileage)	Hoen and Koetse (2014)
	Frequency of long trips	Hidrue et al. (2011)	
	Commuting distance		Qian and Soopramanien (2011)
	Commuting frequency		PHEV: Hoen and Koetse (2014)
Spatial variables			
Charging capability	Having charging facilities at home	Hackbarth and Madlener (2013); Helveston et al. (2015) (China); Hidrue et al. (2011); Hoen and Koetse (2014) *PHEV*: Hackbarth and Madlener (2013)	
	Having a garage		Valeri and Danielis (2015)
Living in urban area		*PHEV*: Musti and Kockelman (2011)	
Countries and regions		Tanaka et al. (2014); Helveston et al. (2015)	
Experience			
Trial period			Jensen et al. (2013)
Social influence			
Market share		*HEV*: Mau et al. (2008)	
Market share in social network			
Positive reviews		Kim et al. (2014); Rasouli and Timmermans (2013)	

Note: If not marked, the effect is on BEV preference.

considered as a "car of the future" (Burgess, King, Harris, & Lewis, 2013; Caperello & Kurani, 2011) or a "work in progress" (Graham-Rowe et al., 2012).

Apart from environmental friendliness and innovativeness, other psychological constructs are also expected to have impacts on EV adoption. Dittmar (1992) and Steg (2005) identified that instrumental, hedonic and symbolic motives influence car purchase and use. Emotions are also found to be significant in some explorative research (Graham-Rowe et al., 2012). These variables are rarely included in choice studies on EV preference. The only example is Helveston et al. (2015) who investigated the symbolic value of BEV: in the US people who attach high symbolic value to their vehicle are more prone to purchasing an EV implying that EV symbolises high social status. In China it is the opposite case.

So far, most studies incorporate psychological factors separately instead of a complete set of constructs in psychological theories such as the theory of planned behaviour (Ajzen, 1991) or other integrative models proposed specifically for pro-environmental or sustainable technology acceptance behaviour (Bamberg & Möser, 2007; Huijts et al., 2012). Should future research wish to add more psychological factors, two points are worth noting: first, it is important to avoid the overlap with factors which are already covered by choice experiments; second, the researcher should control for correlation(s) between different psychological constructs.

4.3. Other variables which are less commonly included

4.3.1. Mobility, residence and car-related condition
A person's EV preferences have also been found to be related to their mobility pattern, residential location and the characteristics of their current and expected car. These variables are however hardly independent as they are usually correlated with socio-economic and psychological factors. Section 4.4 provides a further discussion on this.

4.3.2. Experience
Knowledge of and exposure (through test drive, trial period, etc.) to EV are expected to have an impact on preferences. Jensen et al. (2013) is the only two-wave choice study including an EV trial period. They concluded that exposure to EV through a three-month trial confirmed consumers' worries for EV and had a negative impact on their preference for EV. However, Woodjack et al. (2012) found that drivers gradually adapted their own behaviour to fit the characteristics of EV during the trial period. Bühler, Cocron, Neumann, Franke, and Krems (2014) concluded that experience had a significant positive effect on the general perception of EV and the intention to recommend EV to others, but not on attitudes and purchase intentions.

4.3.3. Social influence
An individual's decisions are expected to be influenced by the behaviour of people in their social network (Kahn, 2007; Lane & Potter, 2007) and social norms which can be regarded as the behaviour of the collective society (Araghi, Kroesen, Molin, & van Wee, 2014). Several qualitative studies found that social influence plays an important positive role in EV promotion (Axsen & Kurani, 2011; Axsen, Orlebar, & Skippon, 2013). Among choice studies, the influence of an individual's social network on HEV adoption has been demonstrated (He, Wang, Chen, & Conzelmann, 2014; Hsu, Li, & Lu, 2013). Social norm has also

been found to be significant: a higher EV market share increases EV preference (Mau et al., 2008). Two studies (Rasouli and Timmermans 2013 and Kim et al. 2014) investigated social influence in EV preference studies. As proxy variables for social influence, they used EV market share among different groups (friends and acquaintances, larger family, colleagues) and the nature (positive or negative) of general public reviews about EV. Both have a significant although minor impact on EV preference.

4.4. Correlation between variables

Most studies explore the interaction between individual-related variables and preference parameters separately without controlling for the correlation between different categories of individual-related variables. One exception is the correlation between psychological factors and other variables: Kim et al. (2014) found psychological factors to be related to socio-economic characteristics, Daziano and Bolduc (2013) with mobility habits and Jensen et al. (2013) with car condition. These studies apply HCM which contains a structural model and facilitates the exploration of relationships between latent psychological constructs and other personal characteristics.

There are certainly more expected correlations: for example, residential locations, mobility habits and car-related conditions are related to socio-economic characteristics; personal norm can also be influenced by social norms (Doran & Larsen, 2016). If these correlations are not controlled for in the final model, the model may suffer from self-selection bias and arrive at incorrect estimates. This may also be the reason for the contradictory findings regarding the effect of socio-economic characteristics on EV preference.

However, including all the variables mentioned above and controlling for all possible correlations may lead to an excessively complicated model and overfitting. Deciding which variables to choose depends on the goal of the research: if one aims to quantify the real effects of variables on EV preference in order to identify the potential factors for policy intervention, correlations should be modelled to derive an accurate effect size. On the other hand, if the study is a market segmentation which aims to study the characteristics of target customers for EV, then only the variables of interest need to be included.

4.5. Conclusion

In general, the effect of individual-specific variables on EV preference remains an open question. Psychological variables are the exception and have a proven stable effect, shown by several studies. For socio-economic and demographic variables, the impact is unclear and sensitive to small changes in model specification. The direction of the effect is also ambiguous since existing evidence is contradictory. Other variables are only included in a few studies, therefore their effects are as yet inconclusive. In most cases, the correlation between all these variables has not been controlled for to avoid self-selection bias. More research is definitely necessary to clarify these currently fuzzy relationships and other methods are needed to add more rigour and confidence to the results.

5. Conclusions, discussion and research agenda

5.1. Main findings

We conduct the literature review in order to identify which attributes of EV and its service system have an impact on the utility of EV, including vehicle attributes, infrastructure system and EV promotion policies. We also aim to find out which individual-related variables affect one's preference for EV. Most research which investigated both of these two topics applied stated choice method since it provides a framework which can easily accommodate the impact of both vehicle attributes and individual characteristics on EV preference.

The impact of financial and technical attributes of EV on its utility is generally found to be significant, including its purchase and operating cost, driving range, charging duration, vehicle performance and brand diversity on the market. The density of charging stations also positively affects the utility of EV, which demonstrates the importance of charging infrastructure development in promoting EV. As for the impact of incentive policies, tax reduction (either purchase tax or road tax) is most likely effective, while there is not yet evidence supporting the effectiveness of other usage cost reduction such as free parking and toll reduction. The findings regarding giving EV access to priority lane vary for studies conducted in different regions. The preferences for the above attributes are mostly heterogeneous and can partially be accounted for by various individual-specific characteristics.

We also synthesised findings regarding the direct effect of various clusters of individual-related variables on one's general preference for EV. The effect of psychological factors is proven to be stable by most studies if included. The results regarding the effect of socio-economic and socio-demographic variables are contradictory thus their effect remains ambiguous. The impact of mobility and car-related conditions of spatial variables, experience with EV and social influence is explored by only a few studies. Although these variables are usually found to be significant, it is still too early for a definitive conclusion. When applying these results it is important to keep in mind that the way in which choice analysis approaches this topic generally lacks methodological rigour since many of them did not control for correlation between these individual-related variables, which may lead to self-selection bias and incorrect estimates for their direct effects.

5.2. Discussion

In this section, we provide a brief integrative discussion regarding the state-of-the-art of EV preference studies. From the conclusion we see that existing studies have generally achieved the same conclusion regarding the significance of financial, technical and infrastructure attributes. As for the effectiveness of incentive policies and the influence of individual-related variables on preferences, hardly any consensus has been reached. We now highlight three issues regarding the general setting and assumption of the reviewed studies which may influence the reliability of their results and conclusions.

First, we think the impact of uncertainty on preference has been insufficiently studied. There have been many other studies in the transportation field highlighting the role of uncertainty, for example focusing on the inclusion of travel time variability in travel

behaviour studies (Li, Tu, & Hensher, 2016). However, all reviewed EV preference studies investigate preferences for alternatives with fixed attribute values even though there are many uncertainties surrounding EV, including battery life, charging facility availability (whether it is occupied by others when needed), depreciation, etc. Moreover, exploratory studies have already found that uncertainty is one of the main barriers for EV adoption (Egbue & Long, 2012). Therefore, excluding the role of uncertainty in choice experiment design and choice model selection may risk reducing realism of choice tasks and ignoring an important factor which affects preference.

Second, most literature did not particularly specify the context of car type choice while it may have an impact on preference. For example, most surveyed studies either only explored preferences when buying a new car or did not distinguish whether the expected purchase was a new or second-hand car. Apart from Chorus et al. (2013) and Hoen and Koetse (2014), none of the studies clarify whether the expected purchase was financed as a private or company car. Furthermore, all reviewed studies only focused on vehicle purchase choice, while other forms of EV adoption may also take place as more mobility business models are becoming widely available, such as private leasing, car-sharing, etc.

Third, it is important to realise that all the studies we found used SP data. Due to the low market share of EV, we can hardly gain any information regarding the unique attributes of EV from actual market data and stated choice is the most commonly used form of data in this case. However, there may be discrepancies between stated choices and real behaviour in actual market, which are termed as "hypothetical bias" (Beck, Fifer, & Rose, 2016). The hypothetical bias may even be accentuated in the case of EV adoption choices since many consumers are not familiar with EV alternatives and its unique attributes (Hess & Rose, 2009). Therefore, studies based on SP data are generally considered to be of less value for estimating market shares, but can still be informative regarding the relative importance of factors for choices (Ben-Akiva et al., 1994). These implications have to be taken into consideration in the interpretation and application of the results of EV preference studies using SP data.

5.3. Research agenda

In this section, we call for further research based on the methodological and content-related limitations of the existing studies.

5.3.1. Improvements on future studies applying discrete choice methods

Regarding experimental design, as stated above the common operationalisation of attributes concerning charging are flawed and should be closer to actual EV use patterns in future choice studies. There are also a wide range of potential policy instruments which can be tested, such as improving home charging availability for people without dedicated parking space, providing dedicated public parking space for EV, closing central urban areas for CVs, assigning car plates without going through a lottery as is the case for CV buyers (already implemented in Beijing, see Zhao, Chen, & Block-Schachter, 2014), etc. Local conditions have to be taken into consideration when choosing the policy attributes to be tested (for example, if traffic congestion is not serious then granting HOV lane access tends to be ineffective). Moreover, in addition to the main effect of increasing sales, potential rebound effects also have to be examined as discussed above.

As for modelling, the interaction effects between several relevant attributes for example, driving range and charging station availability, driving range and charging time, etc. is worth exploring. As for establishing the relationships between individual-related variables and taste parameters, more studies and rigorous methodologies are needed to corroborate the conclusions, such as testing robustness by using different utility functions, applying models which allow indirect relationships apart from direct ones such as structural equation modelling, etc.

Regarding data collection, so far all the EV preference studies are based on SP data. Since the first mass-produced EV entered the market in 2011 and sales have been picking up in several countries (e.g. Norway, Netherlands, etc.), revealed preference (RP) data will become available in the near future. RP data can be combined with SP data in choice model estimation as a source of validation and ASC correction for choice models based on SP data (Axsen, Kurani, McCarthy, & Yang, 2011).

5.3.2. Rethink common assumptions in research

Because all the existing literature investigates EV preference ignored *uncertainties* underlying EV adoption decisions (see above), we recommend that future research investigates the way in which uncertainty influences decisions and quantifies its impact by explicitly incorporating it into a choice experiment, and to use different choice models such as regret models (Chorus, 2010) which may be more suitable for decision-making under uncertainty than random utility maximisation models.

The over-arching assumption in the existing literature is that preferences for EV are static and only a few studies considered *preference dynamics*. Future research could explore better ways to elicit preference variation along with changing social influence, ongoing public debates regarding sustainability issues, technical progress and EV market share changes (innovation adoption) by collecting panel data and integrate these dimensions into a general framework for preference dynamics which can be implemented in system simulations such as agent-based models.

We also call for more attention for the *decision process* of consumers. Choice models assume that the process of decision-making is a black box and that it is rational, while this hardly holds in reality. Klöckner (2014) described an EV adoption decision-making process which describes the volatility of intention over two months. Results contradict the implicit assumption of fixed individual preference in most studies. The extent to which this affects choice model results is currently unknown. Further research can start by exploring how consumers process information when they purchase EV and taking this into account when analysing preferences based on choice data. This would provide more accurate estimations of model coefficients and different policy advice targeting different stages of a decision process.

5.3.3. New perspectives, factors and topics

Adopting a time geography perspective (e.g. Farber, Neutens, Miller, & Li, 2013; Lee & Kwan, 2011; Neutens, Schwanen, Witlox, & Maeyer, 2008) may lead to new insights regarding the effect of activity patterns on EV preferences. Existing research explores the relevance of activity patterns indirectly by including one or a few crude measures such as daily travel distance and linking these with attributes such as driving range and charging availability. Time geography allows for a more integrative and systematic exploration of

constraints imposed by activity patterns. For example, the limited range of EV, charging time and density of charging stations imply constraints and may impact the time-space prisms when driving EV. Researchers can measure the impacts of the use of EVs in their different forms and with different characteristics on these prisms, and explore to what extent destinations fall out of the accessible area permitted by EV and violate the preferred activity patterns of people.

Studies on the effect of *direct experience* with EV are not abundant and provide contradictory results. The increase in demonstration projects and car-sharing programmes enables people to encounter EV in different ways. The effect of different exposure duration (from one ride to a three-month trial period) and types (car-sharing, trials, electrified public transport) on both the perception of EV attributes and purchase intention of EV are worth exploring. Another intriguing topic is the interaction between one's own experience and social influence.

The potential role of *business models* in facilitating EV adoption has been largely overlooked. A stylised economic model (Lim, Mak, & Rong, 2015) found that the option to lease an EV battery can increase the preference for EV. There are a wide variety of business models in addition to battery lease and their effects should be further explored.

Up to now studies have only focused on EV adoption while *EV use behaviour* has hardly been investigated. EV adoption and EV use may each be influenced by different factors. An intriguing topic is the usage pattern of EV in households with multiple vehicles (both EV and CV) and how that evolves over time. Moreover, ignoring EV use after adoption may lead to a serious bias when evaluating policy effects. For example, Shanghai has a strict license plate auction policy (average price 10,000 euro, success rate ∼8%) while EV adopters are guaranteed license plates free of charge. This indeed leads to a higher rate of EV adoption; however, some people may use this policy to obtain a license plate: they buy a PHEV and drive it as a CV and never recharge the battery.[3] These PHEV adoptions do not realise their potential benefits. Therefore, EV use needs to be studied in tandem with adoption to capture the full effect of policies.

Notes

1. Last date of literature search was 15 April 2015.
2. See Section 2.1.
3. http://newspaper.jfdaily.com/jfrb/html/2015-02/03/content_63962.htm,   http://sh.sina.com.cn/news/m/2015-02-03/detail-iawzunex9696715.shtml, last accessed at 23 October 2015.

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