

# Modelling the influence of peers' attitudes on choice behaviour: theory and empirical application on electric vehicle preferences

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## Abstract

While the importance of social influence on transport-related choices is commonly acknowledged within the transport and travel behaviour research community, there remain several challenges in modelling influence in practice. This paper proposes a new analytical approach to measure the effects of attitudes of peers on the decision making process of the individual. Indeed, while most of the previous literature focused its attention on capturing conformity to a certain real or hypothetical choice, we investigate the subtle effect of attitudes that underlies this choice. Specifically, the suggested measure enables us to model the correlated effect that might indirectly affect the individual's choice within a social group. It combines detailed information on the attitudes in the individual's social network and the social proximity of the individuals in the social network. To understand its behavioural implications on the individual's choice, the *individual's peer attitude* variable is tested in different components of a hybrid choice model. Our results show that the inclusion of this variable indirectly affects the decision making process of the individual as the peers' attitudes are significantly related to the latent attitude of the individual. On the other hand, it does not seem to directly affect the utility of an alternative as a source of systematic heterogeneity nor does it work as a manifestation of the latent variable, i.e. as an indicator.

*Keywords:* Social influence; correlated effects; social network; individual's peer attitudes; hybrid choice models; electric vehicle preference.

## 1. Introduction

People influence each other in everyday life. The words and actions of an individual may well affect the thoughts, intentions and actions of other individuals and, consequently, their decision making process. Over the last years, travel behaviour researchers and demand analysts have become increasingly aware of the effects of social influence on transport and travel behaviours and proposed different measures to account for these effects in quantitative models. However, social influence is a vast and articulated concept. It can be defined as the sum of various forms of reciprocal and non-reciprocal interactions, and of behavioural and cognitive factors that lead to changes in an individual's thoughts and behaviours (Forgas & Williams, 2001; Rashotte, 2007). As explained by Cialdini & Goldstein (2004), social influence is manifested through two

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1 main processes: conformity and compliance. Conformity involves behavioural changes in an individual that  
2 wants to match the behaviours of others while compliance involves a behavioural change as a response to  
3 others' requests, which can be a direct solicitation or indirect pressure from social norms. Describing the  
4 process of influencing as complementary to the process of accepting influence, Ng (1980), defined three  
5 levels of influence. The first level is the more well-studied form of influence, direct influence, which is  
6 generated by influencing agents with face-to-face interactions. The second level of less direct influence  
7 comes from the manipulation of social values and norms. Both the first and second level are subject to the  
8 phenomena of resistance and reinforcement. Instead, these phenomena are absent at the third level of  
9 influence. This is the level of indirect influence, where the information exchange is indirect or not  
10 identifiable. Thus, it might be very difficult to explain the moment when others affect the individual because  
11 s/he is not even aware of it.

12  
13 These social influence processes have extensively been studied in different fields such as sociology, social  
14 psychology and economics. Drawing upon these disciplines, transportation researchers developed  
15 quantitative models to include the effect of such processes. For instance, among the seminal papers which  
16 inspired the previous transport modelling literature, particular attention was paid to Brock & Durlauf (2001)  
17 who introduced social interactions in discrete choice models (DCMs) by relaxing the assumption of the  
18 independent individual as described in neoclassical economics. They originally proposed a model where the  
19 utility of an individual of a pre-determined social group is directly related to the choices of the people in that  
20 group. As a direct consequence of this pioneering work, we see several models of travel behaviour and  
21 residential location choice that consider social influence effects through the introduction of an explanatory  
22 variable taking into account the actions and choices of other people (Dugundji & Walker, 2005; Páez et al.,  
23 2008; Walker et al., 2011). Several studies in the transport literature have presented modelling  
24 methodologies for the inclusion of the different social influence processes. In accordance to the classification  
25 proposed by Manski (1993), Maness et al. (2015), b) contextual effects or compliance, such as the influence  
26 generated by injunctive norms analysed by Cherchi (2017), and correlated effects such as attitudes and  
27 homophily effects that do not involve direct behavioural inputs from others. Another important related topic  
28 that has been analysed in transport literature is the social network of which the individual is a member. A  
29 social network can be defined for each individual (or ego) as the set of peers (or alters) who have a  
30 relationship with that individual (Carrasco & Miller, 2006). ). The relationships between ego and alters are  
31 also called ties and characterise the interaction matrix employed by researchers for the analysis of social  
32 networks. Indeed, the elements of this matrix are a measure of the 'strength of the tie', which represents the  
33 type of relationship between the individuals, such as social proximity or frequency of interaction (Carrasco  
34 & Miller, 2006; Carrasco et al., 2008). Social networks have widely been used as a source to explore  
35 activity-travel decisions (Carrasco et al., 2008; Frei & Axhausen, 2009; van den Berg et al., 2013) and social  
36 influence on the individual's behaviour (Pike, 2014; Kim & Parent, 2016).

37  
38 However, there remain many challenges in modelling social influence in practice. For instance, when the  
39 analysis of social influence is undertaken by including the peers' choices in the model, it seems reductive not  
40 to consider attitudes and assessments which contribute to the formation of the intentions and, therefore, the  
41 choices. This is far more complex and directly concerns what contributes to forming those choices, such as  
42 attitudes and beliefs (Ajzen, 1991). Indeed, the effects generated by the attitudes in an individual's social  
43 network can be classified as part of correlated effects (Manski, 1993) arising when an individual behaves  
44 like the other members within a group or institutional environment as a result of homophily, values and,  
45 indeed, attitudes (Maness et al., 2015). In a step towards this direction, Kamargianni et al. (2014) proposed a  
46 new modelling approach that accounts for social influence effects on attitudes rather than assuming a direct  
47 impact on the utilities. Using a range of direct questions posed to teenagers, Kamargianni et al. (2014)  
48 elicited teenagers' perceptions of their parents' attitudes towards walking and cycling. The answers to these  
49 questions were used as indicators of a latent variable, which defines the teenager's 'social environment'. The  
50 latent variables representing the attitudes were embedded within a hybrid choice model (HCM) of travel  
51 modes. Nevertheless, the use of this latent construct to capture social influence effects seals all the most  
52 interesting questions about the decision making mechanisms affected by social influence in a 'black-box'.  
53 Moreover, eliciting the perceived attitudes of others through direct statements has a major disadvantage: it  
54 requires additional questions and adds a cognitive bias that is typical of questions potentially perceived as a  
55 judgement of related others (e.g. courtesy bias, Jones, 1993). This bias can be potentially addressed by  
56 undertaking a more detailed and qualitative survey procedure as in Axsen & Kurani (2011). The multi-

1 method research instrument developed by Axsen & Kurani (2011) generates several deep insights into social  
2 influence processes but has not far been translated into the mathematical modelling on choice behaviour.

3  
4 This paper contributes to the body of literature on modelling the specific effects of social influence generated  
5 by the attitudes of peers' groups. We propose a social influence measure, the *individual's peer attitude* (IPA)  
6 variable, which makes it possible to model the correlated effect generated by peers' attitudes indirectly  
7 influencing the individual's choice. This measure combines detailed information, collected through Axsen  
8 and Kurani's (Axsen & Kurani, 2011) multi-method research instruments, which regards the attitudes in the  
9 individual's social network and the social proximity of the individuals in the social network. This is done to  
10 derive the attitudes and preferences prevalent within an individual's social network directly from the  
11 members of that social network. This analytical modelling approach has two main benefits. First, the IPA  
12 variable is a direct measure elicited from the peers about their attitudes and avoids both the self-reported  
13 elicitation of social influence from peers and the elicitation of the individual's perception of his/her peers'  
14 attitudes. This is especially important in the context of a new technology where observed choices are often  
15 limited and it is not as easy to understand how people conform to others' choices. Secondly, we explore the  
16 role of this measure in the decision making process of an individual. We present a systematic analysis of  
17 how to best specify an HCM to capture the effects of the IPA variable. In particular, we use three HCM  
18 specifications to test whether the IPA variable a) directly affects the utility of an alternative as a source of  
19 systematic preference heterogeneity; b) affects the unobserved component of the utility of an alternative by  
20 explaining (part of) the covariance of a latent attitude; or c) represents a manifestation of such a latent  
21 attitude, i.e. it is an indicator of the latter, albeit 'indirect' as it is elicited indirectly from peers' attitudinal  
22 indicators instead of from a 'direct' response of the individual.

23  
24 The analysis in this paper is undertaken within the empirical context of vehicle type choice, using a dataset  
25 on electric vehicle (EV) stated preferences. Previous transport research showed the importance of modelling  
26 social influence effects to explore EV adoption (Walker et al., 2011; Rasouli & Timmermans, 2013; Kim et  
27 al., 2014; Cherchi, 2017). To achieve this aim, some of these studies, such as Kim et al. (2014) and Cherchi  
28 (2017), have employed the HCM as the modelling methodology. More generally, the HCM model has been  
29 largely used to model EV purchase and use behaviour as it supports the inclusion of latent variables  
30 manifested by psychometric and unobservable measures such as pro-environmental preferences, status  
31 symbol, new technology, and safety (Bolduc et al., 2008; Daziano & Chiew, 2012; Jensen et al., 2013). The  
32 data used for this study was collected as part of a study undertaken and published by Axsen et al. (2013),  
33 though this particular subset of the data was not investigated in that paper. It was collected in a technology-  
34 based workplace in the UK where some members of the staff previously took part in a 'Battery Electric  
35 Vehicles' (BEV) experience. According to earlier analyses shown in Axsen et al. (2013), the majority of  
36 participants stated that their BEV perceptions were "highly influenced" by at least one social interaction  
37 among colleagues. Therefore, this specific context makes it possible to study a social network that includes  
38 "high-tech" individuals of which some had direct exposure to the technology and others did not.  
39 Nonetheless, in researching technology adoption in other technology-based contexts, the influence of co-  
40 workers has been found to be particularly important when the individuals are in fact exposed to the new  
41 technology at the workplace (Lewis et al., 2003; Eckhardt et al., 2009). Besides the investigation of  
42 preferences between a conventional car and an electric car, the dataset provides very extensive information  
43 on three sociological constructs, lifestyle practices, lifestyle liminality and environmental concern (the New  
44 Ecological Paradigm or NEP) and the tie strengths in the specific context of a workplace. Nonetheless, the  
45 data has the advantage that almost all the colleagues named by each respondent were also surveyed. The  
46 resulting social network has all to be considered a complete network. All these sets of information are  
47 fundamental to build the IPA variable related to this specific context.

48  
49 The rest of this paper is structured as follows. Section 2 briefly summarises the current literature on  
50 modelling the effect of social influence on transport choices, highlighting the challenges modern researchers  
51 are still facing and presents conceptual framework and hypotheses. Section 3 presents the data and the  
52 methodology adopted in this research. Section 4 presents and discusses the substantive results, and Section 5  
53 concludes the paper.

## 2. Background and motivations

To clarify the sources of social influence generating similar behaviours within a group which can be quantified and tested in a model, Manski (1993) gave a useful conceptual definition of the social influence and its effects. Indeed, trying to identify endogenous social effects in a linear regression model, he classified three different sources of influence: (a) conformity or endogenous effects, when a person follows the most recurrent actions in the group, (b) compliance or contextual effects, when a person is influenced depending on exogenous characteristics of the group, and (c) correlated effects, when a person behaves like the other members of the group to which he/she belongs (e.g. workplace, residential neighbourhood). Along the same lines, the pioneering works of Brock & Durlauf (2001) developed a model that quantifies of endogenous social influence effects generated by social interactions in the decision making process of the individual. Brock & Durlauf (2001) stated that the utility of an individual of a determined social group is directly related to what people of that group choose. Thus, the utility of an individual is a function of all possible actions (i.e. choices) of the individual's peers (a further extension of this model was discussed in Durlauf & Ioannides (2010)). Different from Manski (1993), Brock & Durlauf (2001) accounted for conformity in a DCM rather than a linear model.

On the other side, focusing the attention on the importance of the social network characteristics and the connections within this network, Leenders (2002) built a model in which an individual determines his/her behaviours and opinions considering the connection with the influencing peers of his/her network. Thus, the interdependence between peers defines the context. This interdependence was accounted in an autocorrelation model using an interaction matrix that measured the "nearness" of the people inside a group. While Leenders (2002) defined the weight matrix which gives information about the strength of the tie between an individual and peers, in Brock & Durlauf (2001), this matrix is not present as they assumed a constant strategic complementarity between an individual's choice and the peers' choices which are included as an average value.

These seminal works have had a significant impact on the modelling methods used later on to include social influence in transport and travel behaviour literature. Many of these works extended and integrated the approaches proposed by Brock & Durlauf (2001) and Leenders (2002), and mainly focused their attention on analysing and modelling endogenous social influence effects, i.e. conformity processes (Maness et al., 2015). For instance, Dugundji & Walker (2005), Dugundji & Gulyás (2008) and Walker et al. (2011) defined social influence as an explanatory variable which takes into account the percentage of the individual's neighbours who made a specific choice and is included in a DCM considering social and spatial network interdependency. Instead, Páez et al. (2008) presented a dynamic DCM accounting for the combination of the previous actions of the individual's peers and the social distance (or strength of the tie).

Nonetheless, some studies in transport research have included social influence in more complex model specifications (i.e. the HCM<sup>2</sup>), as a means of capturing the processes of social conformity. Kim et al. (2014) included social influence as an explanatory variable into the utility function of an HCM to explore the demand for EVs. Latent variables were used to capture the attitudes of the individual, towards technology, innovation and environment, while the social influence variable took into account the extent to which EVs were chosen within the individual's social group. This technique essentially allowed them to explore the extent to which existing market shares could influence individual's choices, especially when considering the market shares within his/her social group at different degrees of closeness. Another recent measure of social influence was also used by Kim et al. (2017) to analyse a different case study, the car-sharing, with a hybrid random utility-maximization and random regret minimisation model. In this case, the social distance variable is more elaborated than in their previous work (Kim et al., 2014). The choice of others is weighted by the social distance specified as a latent variable. This latent variable is characterised in the structural model component by socio-demographic variables and frequency of contacts while the measurement model component is a function of the social closeness (i.e. indicators). Nevertheless, these approaches to measure social influence does not fundamentally differ much from the approaches described by Dugundji & Walker (2005) and Páez et al. (2008), as the social influence is limited to a different version of conformity as a function of the adoption rate within the social network.

<sup>2</sup> More specific details on HCM structure can be found in subsection 3.2

1  
2 A more insightful work on combining social influence and attitudes influencing the decision making process  
3 is that one of Kamargianni et al. (2014). They specifically extended the HCM methodology to incorporate  
4 social influence as a latent variable. To investigate the travel choices of elementary school children and  
5 teenagers for their school trips, the authors considered a latent variable to represent the unobservable  
6 perceptions and attitudes of the decision-maker and included in it the unobserved effects of the “social  
7 environment” of the individuals (i.e. the social environment of a child concerned the attitudes of parents  
8 towards specific transport modes). This methodology relies on gathering extra information of what children  
9 and teenagers think or perceive of their parents’ attitudes and ignores the actual (revealed) attitudes towards  
10 walking of parents. Always employing an HCM specification, Cherchi (2017) built a model accounting for  
11 both compliance and conformity effects. For example, a measure of compliance effects could be considered  
12 the latent variable to account for “injunctive norms” when positive or negative thoughts of others concerning  
13 a certain behaviour affect the individual in performing that behaviour. Nonetheless, the author also included  
14 in the model variables measuring “social signalling”, which is manifested when an individual modifies  
15 his/her behaviour in order to convey a certain image to others of himself/herself, and “descriptive norms”,  
16 which is manifested when individual's actions are influence by real or possible actions of others in the same  
17 context (i.e. a measure of conformity to hypothetical social adoption).

18  
19 Recently, other papers have enriched the discussion on measuring social influence in DCMs. For instance,  
20 (Pan et al., 2019) modelled the effect of conformity, given by stated choices of peers, in a sequential stated  
21 preference experiment where respondents were informed of the choice of others in his/her social network.  
22 Always undertaking a sequential stated preference experiment, Manca et al. (2019) modelled the effect of  
23 real social interaction with the exchange of information within a social network in a state-dependent dynamic  
24 choice model.

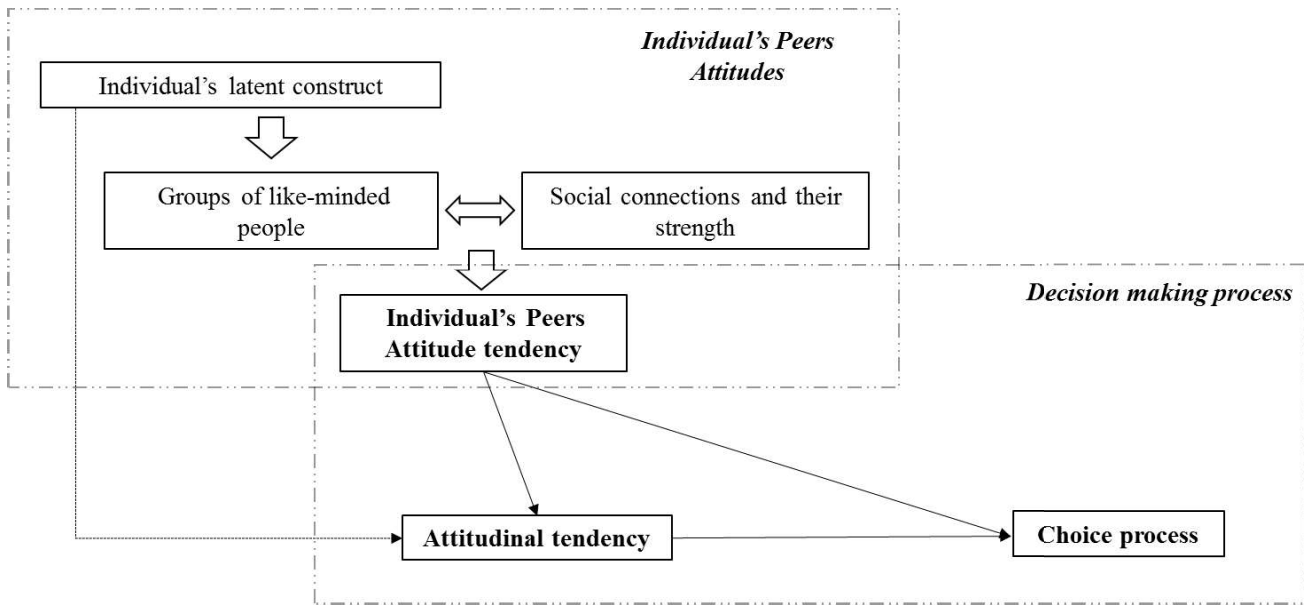
25  
26 Although there have been significant advancements on measuring the effects of social influence, most of the  
27 formulations described above are limited to capturing conformity to a certain choice, without addressing the  
28 mechanisms by which attitudes and opinions of others affect one’s choice. None of them has quantitatively  
29 tested the possibility that peers’ attitudes may (a) generate correlated environmental and individual-level  
30 effects (Manski, 1993; Maness et al., 2015), (b) indirectly affect or be affected by peers and, consequently,  
31 (c) affect the decision making process. Indeed, individuals like to interact with like-minded people and tend  
32 to select their peers based on what they believe are the attitudes/opinions of those peers (Mäs & Flache,  
33 2013), while simultaneously being prone to copy attitudes/opinions from those peers (Flache et al., 2017).  
34 This positive feedback loop is well-known to lead like-minded people to cluster together in a society  
35 (Friedkin & Johnsen, 2011). This gives a strong case to argue that (as the outcome of a long term  
36 societal/evolutionary process) the expressions of peers’ attitudes can influence or be influenced by the  
37 attitude of the individual. However, in everyday life, individuals do not necessarily directly observe the  
38 attitudes and the opinions of others nor frequently exchange information about them (Tang & Chorus, 2019).  
39 This is strictly linked to the indirect influence illustrated by Ng (1980) like the subtle effects of attitudes in a  
40 social network might affect an individual’s decision making process.

41 This paper proposes a model formulation that quantifies the correlated effects generated by peers’ attitudes  
42 affecting individual preferences. Unlike previous studies, we neither focus exclusively on how people  
43 conform to the choices (or hypothetical choices) made by the peers nor do we build the social influence  
44 variable on the respondent’s perception of peers’ attitudes. Instead, we propose a methodology to  
45 simultaneously take into account the attitudes of the individual, as well as the stated attitudes of the peers in  
46 his/her social network, and information on the tie strengths within the social network.

## 47 48 49 50 *2.1 Conceptual framework*

51  
52 The conceptual framework (Figure 1) enables to visualise how attitudes of peers are defined and how it is  
53 hypothesised to affect the decision making process of the individual.

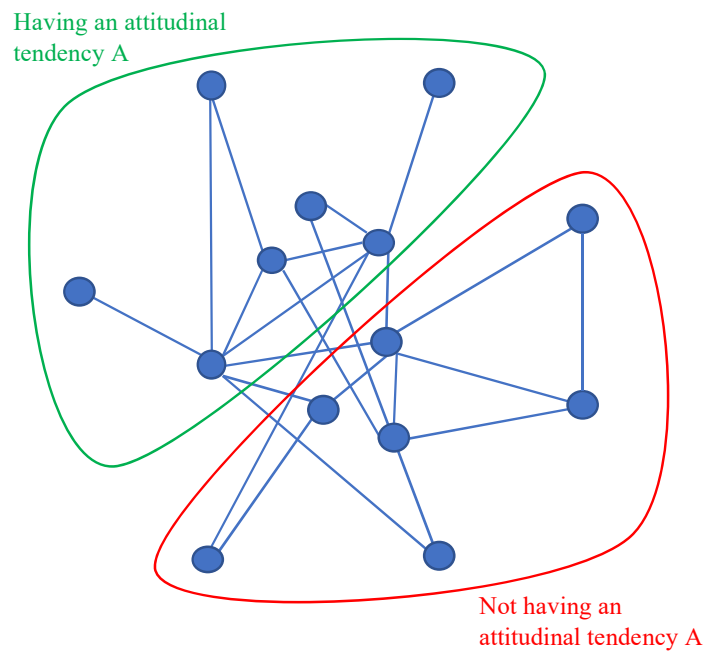
1 *Figure 1: Conceptual Framework*



2  
3  
4 As indicated on the top left side of Figure 1, the specification of the IPA variables involves different steps:

- 5 1. To identify the individual's latent constructs, the attitudinal latent constructs of the respondents are investigated using factor analysis of psychometric indicators.
- 6 2. Considering the correlated indicators defining each latent construct, cluster analysis is performed on these attitudinal items that characterise each latent construct to identify groups of like-minded people who are, in other words, the contacts in each individual's social network that have a certain attitudinal tendency (e.g. environmentally friendly, open to innovation, sceptical, etc.).
- 7 3. Moreover, social connection and their strength within the social network are identified with the help of the interaction matrix.
- 8 4. Finally, the IPA variable captures the combination of information regarding the social connections with their specific attitudes, which result from the three steps above. Therefore, the influence generated by the attitudes of peers arises as a result of individuals belonging to a cluster of a certain attitudinal tendency (i.e. like-minded) and being connected to others also characterised by that attitudinal tendency (Figure 2).

1 *Figure 2: Combination of social connections and attitudinal clusters defining like-minded individuals*



2  
3

4 Assuming that individuals with a specific attitudinal tendency  $A$  could influence (or be influenced by) peers in  
5 their social network during the decision making process (see bottom right part of Figure 1), we explored  
6 different HCM formulations accounting for psychometric measures of each individual (i.e. the latent variables)  
7 together with the measure of the peers' attitudes (i.e. the IPA variable). The aim is to test the three following  
8 hypotheses:

9

10 H1. The IPA variable has a direct effect of the peers' attitudes on the utility function. The individual's peer  
11 attitudes affect the utility (i.e. preferences) as a simple characteristic of the individual to capture  
12 unobserved heterogeneity explaining the decision making process.

13

14 H2. The IPA variable characterises the latent attitudinal characteristics of the individuals and, therefore,  
15 indirectly affects the utility by explaining (part of) the covariance of the attitudinal latent construct.

16

17 H3. The IPA variable is an indirect manifestation of the underlying latent attitudinal characteristics of the  
18 individual.

19

### 20 **3. Modelling methodology**

21

22

23 This section illustrates how to develop mathematically the IPA variables and how this variable is included in  
24 various HCM formulations to test the hypotheses.

25

#### 26 *3.1 IPA variable specification*

27

28 Let the social network graph be represented as  $(N, \omega)$ , where  $N = \{1, 2, \dots, i, j, \dots, m, \dots, n\}$  is the set of the  
29 nodes (contacts in the social network) and  $\omega_{ij}$  is the element of the interaction matrix;  $W$  representing the  
30 relations between nodes  $i$  and  $j$ , where  $W = [n \times n]$  and  $n$  is the total number of individuals.  $\omega_{ij}$  is the  
31 weight representing the strength of the tie between individuals  $i$  and  $j$  (e.g. the social proximity).  
32

1 For the all set of nodes  $N$ , factor analysis is performed to identify the correlation among the psychometric  
 2 statements characterising the individual latent construct. Having identified the subset of indicators specific to  
 3 each latent construct, cluster analysis on such indicators is undertaken to group respondents  $j$  with similar  
 4 indicator levels for specific factors.

5  
 6 Once the attitudinal clusters (Figure 2) are defined, to specify mathematically the social influence variable,  
 7 the following procedure has been applied.

8  
 9 Firstly, considering each connection  $j$  classified according to the results of cluster analysis on the correlated  
 10 psychometric statements defining each latent variable, the element  $g_j$  of the dummy variable vector  $g =$   
 11  $[1 \times n]$  equals 1 if an individual  $j$  belongs to a cluster with a certain tendency  $A$ , 0 otherwise:  
 12

$$g_j = \begin{cases} 1 & \text{if individual } j \text{ is a person with an attitudinal tendency } A \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

13  
 14 Secondly, the scalar product of the interaction matrix and the dummy variable vector for an attitudinal  
 15 tendency  $A$  defines the matrix  $F = W \cdot g = [n \times n]$ . Each element  $f_{ij}$  of the matrix  $F$  is defined as follows:  
 16

$$f_{ij} = \begin{cases} \omega_{ij}g_j & \text{if } j \text{ is a peer with an attitudinal tendency } A \text{ of } i\text{'s social network, where } i \neq j \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

17  
 18 With the help of the interaction matrix, two types of variables have been specified and tested in the model: in  
 19 its continuous form, the  $IPA_i$  can be defined as a weighted sum of the number of  $m$  peers (within a social  
 20 network of individual  $i$ ) who fall into a cluster characterised by certain attitudinal tendencies  $A$  (Eq 3);  $IPA_i^d$   
 21 is the dummy variable to take into consideration of a maximum value above a certain limit (Eq 4), such as  
 22 the average value of  $IPA$  for the whole social network,  $\overline{IPA} = \frac{\sum_{i=1}^n IPA_i}{n}$  where  $n$  is the total number of nodes  
 23 in the network as described above.  
 24  
 25

$$IPA_i = \sum_{j=1}^m f_{ij} \quad (3)$$

$$IPA_i^d = \begin{cases} 1 & \text{if } IPA_i \geq \overline{IPA} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

26  
 27  
 28 Thus, the  $IPA$  is a function of both personal attitudes ( $g_{ij}$ ) and individual's social network, through the  
 29 interaction matrix ( $W$ ).  
 30

31 In the continuous  $IPA_i$  variable, the weights are driven by the strength of the tie between the individuals and  
 32 his/her peers. Thus, the  $IPA$  variable score is larger when the number of peers that are characterised by a  
 33 certain attitude is also larger and/or when these peers are closer to the individual (i.e. the tie strength is  
 34 larger).  
 35

36 The methodology could be applied and generalised to all the latent constructs identified during the  
 37 exploratory factor analysis on the available statements.  
 38  
 39

### 40 3.2 Incorporation of the social influence variable in a choice model

41  
 42 The variables specified in the above subsection (Eq 3 and Eq 4) have been incorporated in the equations of  
 43 following subsection (Eq 5, Eq 6 and Eq 7) to investigate the research objective by extending the HCM  
 44 model to include social influence impacts.



This type of discrete choice model formulation enables the analyst to take into account the cognitive and psychological aspects of the individual (Vij & Walker, 2014). Although they are not observable in the same way as the attributes characterising the alternatives, these cognitive and psychological aspects can be incorporated in the model by defining one or more latent variables. The latent variables are typically identified through the analysis of psychometric scale survey questions. The HCM has been extensively used in transport literature in recent years for the analysis of travel behaviour and transport demand. They have also been criticised for their use in predicting transport policies, especially when using cross-sectional datasets (Chorus & Kroesen, 2014). However, in this study, the HCM is not employed for long term forecasting, but rather to understand and explain the heterogeneity in the decision making process of the individual. Therefore, given that it supports the inclusion of psychometric and other unobservable measures, the HCM specification is very suitable for the purpose of this study. Indeed, the HCM formulation has also been demonstrated to have benefits such as enabling the identification of structural relationships between observable and latent variables to support practice and policy (Vij & Walker, 2016).

From a mathematical point of view, the utility  $U_{air}$  associated with alternative  $a$  in the stated preference task choice  $r = [1, \dots, R]$  by the individual  $i$  is given by:

$$U_{air} = ASC_a + \beta_{aX}X_{air} + \beta_{aS}S_i + \beta_{aAtt}Att_i + \eta_{ai} + \varepsilon_{air} \quad (5)$$

where  $X_{air}$  is a vector of the attributes of the alternative,  $S_i$  is the vector of individual socioeconomic characteristics,  $Att_i$  is the latent construct (or vector of latent constructs, more generally),  $\beta_{aX}$ ,  $\beta_{aS}$  and  $\beta_{aAtt}$  are the respective vectors of parameters to be estimated,  $ASC_a$  is the alternative-specific constant. The error term  $\varepsilon_{air}$  is assumed to be identically and independently distributed extreme value type 1 (EV1), while the noise  $\eta_{ai}$  is an error component assumed to be normally distributed  $N(0, \sigma_\eta)$  and intended to capture panel effects.

In accordance with Walker (2001) and Ben-Akiva et al. (2002), the latent variable is defined by two different components. The first is the structural model component, which associates the latent variable to socioeconomic characteristics of the individual  $i$ :

$$Att_i = c + \delta S_i' + \eta_{ai} + \gamma_i \quad (6)$$

where  $\delta$  is the vector of parameters associated with the socioeconomic characteristics,  $c$  is the intercept and  $\gamma_i$  is the error term assumed to be normally distributed  $N(0, \sigma_\gamma)$ .  $\eta_{ai}$  is the error component distributed  $N(0, \sigma_\eta)$  which is in common with the choice model component at Eq 5 (Bierlaire, 2016; Sottile et al., 2018).

The second component is called the measurement model component and allows, for each individual  $i$ , to link the latent variable to the indicators through  $f$  equations, hence to the indicators  $I_{fi}$ :

$$I_{fi} = d_f + \theta_f Att_i + \mu_{fi}, \quad \text{with } f = 1, \dots, F \quad (7)$$

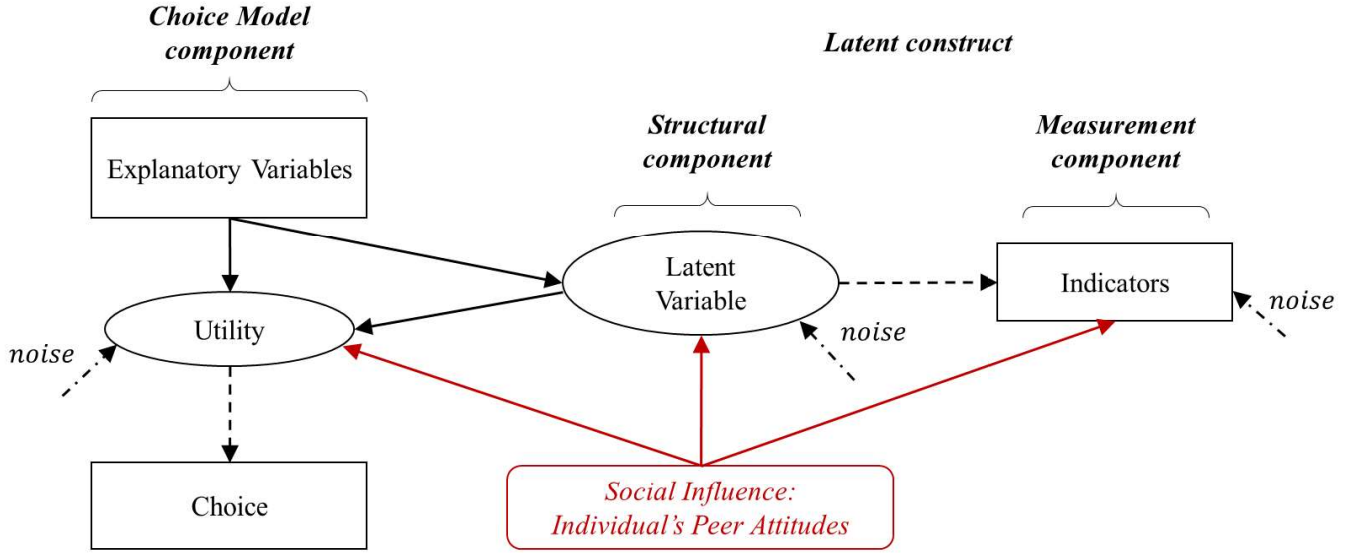
where  $\theta_f$  is the coefficient characterising the latent variable,  $d_f$  is the intercept and  $\mu_{fi}$  is the error term assumed to be normally distributed  $N(0, \sigma_\mu)$ . To be able to identify the mathematical problem, for the first indicator,  $d_f$  is set equal to 0 and  $\theta_f$  is set equal to 1, following the normalisation of Ben-Akiva et al. (2002).

The probability of individual  $i$  choosing a set of alternatives  $a^r = (a^1, \dots, a^R)$  during the  $R$  choice tasks is given by the product of the conditional probability of choosing  $a$  in task  $r$ ,  $P_{air}(\eta_{ai}, \gamma_i)$ , and the conditional distribution function of the indicators,  $g_{I_f}(I_{fi} | Att_i(\gamma_i))$ , all integrated over the distribution of  $\eta_i$  and  $\gamma_i$  (Jensen et al., 2013):

$$P_{a^r i}(\eta_{ai}, \gamma_i) = \int_{\eta, \gamma} \prod_r P_{air}(\eta_{ai}, \gamma_i) g_{Att}(\gamma_i) \prod_f g_{I_f}(I_{fi} | Att_i(\gamma_i)) g(\eta) g(\gamma) d\eta d\gamma \quad (8)$$

1 The effect of social influence resulting from the peers' latent attitudes is included in three different  
 2 components of the HCM (Figure 3).  
 3  
 4

5 *Figure 3: Inclusion of social influence in HCMs (adapted from Ben-Akiva et al. (2002) and Kim et al.*  
 6 *(2014))*



7  
 8  
 9  
 10  
 11 The following HCM formulations reflect different mechanisms in the decision making process by which the  
 12 individual's peer-attitude variable operates in the determination of preferences and attitudes: as explanatory  
 13 variable in preference determination (Eq. 9); as component explaining the variance of the latent constructs  
 14 (Eq. 10); as an indicator manifesting the latent construct (Eq. 11):  
 15

16 In Formulation 1, the variable has been included in the choice model component to test the first hypothesis  
 17 (H1):  
 18

$$\begin{aligned}
 U_{air} &= ASC_a + \beta_{aX}X_{air} + \beta_{aS}S_i + \zeta_{asI}IPA_i + \beta_{aAtt}Att_i + \eta_{ai} + \varepsilon_{air} \\
 Att_i &= c + \delta S'_i + \eta_{ai} + \gamma_i \\
 I_{fi} &= d_f + \theta_f Att_i + \mu_{fi}
 \end{aligned}
 \tag{9}$$

21  
 22  
 23 In Formulation 2, the IPA variable has been included in the structural model component to take into  
 24 consideration the latent influence of peers on the individual's attitudes and test the second hypothesis (H2):  
 25

$$\begin{aligned}
 U_{air} &= ASC_a + \beta_{aX}X_{air} + \beta_{aS}S_i + \beta_{aAtt}Att_i + \eta_{ai} + \varepsilon_{air} \\
 Att_i &= c + \delta S'_i + \psi IPA_i + \eta_{ai} + \gamma_i \\
 I_{fi} &= d_f + \theta_f Att_i + \mu_{fi}
 \end{aligned}
 \tag{10}$$

26  
 27  
 28  
 29  
 30  
 31 Finally, with the inclusion of the social influence variable as an additional "indirect" indicator in the  
 32 measurement model component (Formulation 3), we can explore the third hypothesis (H3):  
 33

$$U_{air} = ASC_a + \beta_{aX}X_{air} + \beta_{aS}S_i + \beta_{aAtt}Att_i + \eta_{ai} + \varepsilon_{air}$$

$$Att_i = c + \delta S_i' + \eta_{ai} + \gamma_i \quad (11)$$

$$I_{fi} = d_f + \theta_f Att_i + \mu_{fi}$$

$$IPA_i^d = d_{IPA} + \theta_{IPA} Att_i + \mu_{IPAi}$$

This third formulation (Eq 11) does not follow the regular approach of defining the measurement model. This is generally defined with a more ‘rigorous’ approach (i.e. exploratory factor analysis). Instead, we use an “indirect” indicator to define an additional indicator that does not refer to a direct response of the individual to certain questions, but it refers to the responses of his/her peers. The individual  $i$  does not claim knowledge of peer  $j$ 's attitudes a priori. Hence, we would like to investigate whether the standard indicator response and the responses of particular contacts forming  $i$ 's social network are both manifesting the same individual's latent construct.

The models of this paper have been estimated through a simulated maximum likelihood calculation with the help of PythonBiogeme (Bierlaire & Fietarison, 2009). 2000 quasi-random draws have been generated through Modified Latin Hypercube Sampling (MLHS) approach (Hess et al., 2006).

## 4. Empirical application

The approach has been tested on the empirical context of electric vehicle (EV) adoption intentions, using data from a stated preference survey on vehicle preferences. Besides this stated choice experiment data, the dataset provides extensive information on social relationships amongst the respondents and sociological constructs such as lifestyle practices, lifestyle liminality and the New Ecological Paradigm.

### 4.1 Data

Specifically, the data used in this paper was collected between 2010 and 2011 in a workplace of 500 employees in northwest England. 57 of them had previously participated in a study called the 'Battery Electric Vehicles (BEV) project'. First, 192 employees completed a ‘screener’ survey, of which, 21 were selected for in-depth semi-structured interviews on respondent perceptions, preferences and patterns of social influence regarding EV – the analysis was published elsewhere (Axsen et al., 2013). As part of this same project, researchers implemented a second, more detailed survey with four main parts: next planned vehicle purchase (a stated choice experiment), household energy, social connections with co-workers and others, engagement in lifestyle practices, and demographic information. This survey was completed by 105 employees at this same workplace.

The survey included a state preference (SP) design of which the experimental design comprised 3 levels for each of the 4 alternative attributes. This  $3^4$  factorial design was simplified to a ‘main-effects only orthogonal fractional design’ of 9 different exercises choosing between conventional vehicles (CV) and electric vehicles (EV) as shown in Table 1. This is the same factorial design used in the analysis of the interview data in Axsen et al. (2013).

1

*Table 1: SP experiment (source Axsen et al. (2013))*

	Vehicle choice	
	Conventional Vehicle	Electric Vehicle
<b>Price (UK£)</b>	CV price	100% CV price
		110% CV price
		125% CV price
<b>Acceleration</b>	CV acceleration	75% CV acceleration
		100% CV acceleration
		125% CV acceleration
<b>Driving range (miles)</b>	450 miles	75 miles
		125 miles
		175 miles
<b>Recharge/refuel time</b>	5 minutes	5 hours
		10 hours
		15 hours

2

3 It is important to notice that, since the data collection occurred in 2011, new EV technology has emerged  
4 and, therefore, there might be different baseline perceptions among some consumers. However, the SP  
5 experiment tests a range of attribute levels (for range, purchase price, recharge time), where tradeoffs in  
6 those attributes are still relevant today. That is, EVs on the market still present a range of prices, EV driving  
7 ranges, and their recharge time varies considerably by battery size and charge speed (Level 1 through DC  
8 Fast Charging). Nonetheless, the paper uses EVs as a case study for the systematic analysis regarding the  
9 inclusion of social influence using different HCM structures. Indeed, such a case study was at one place  
10 (UK), and time (2011) with a particular iteration of EVs. Accordingly, we do not intend for our results to be  
11 interpreted into any universal findings on EVs or social influence for that matter.

12

13 The survey also included 30 questions on respondent characteristics which we generally describe as  
14 ‘attitudes’, but include several constructs. Sixteen questions were on respondent engagement in different  
15 lifestyle practices, where respondents indicated their frequency of engagement in each of the 16 activities.  
16 Axsen et al. (2012) developed this scale as part of lifestyle theory, which explores how consumer interest in  
17 new technologies may relate to their engagement in lifestyle, or packages of related behaviours that also  
18 connect to their self-identify (Giddens, 1991). Applications of lifestyle theory find that engagement in  
19 environment- and technology-oriented lifestyles can be positively associated with interest in EV (Axsen et  
20 al., 2015; Axsen et al., 2016). Another six survey questions related to lifestyle openness of ‘liminality’, also  
21 first implemented in a survey format by Axsen et al. (2012), where higher liminality tends to be associated  
22 with interest in buying an EV (Axsen et al., 2013). The final eight questions are part of a well-cited scale of  
23 environmental concern, the New Ecological Paradigm (NEP) (Dunlap et al., 2000), which researcher  
24 frequently combine into a single composite variable representing environmental interest.

25

26 The dataset used for this study has been cleaned to have complete and accurate records for model estimation.  
27 Firstly, taking into consideration all the 105 respondents who completed the questionnaire, missing  
28 information on age and income has been imputed for 10% of the 105 respondents. This automatic multiple  
29 imputation has been calculated using a linear regression which accounted for education, occupation, gender,  
30 marital status, number of persons in the household, number of cars in the household, parking space as  
31 independent variables. Secondly, inaccurate records have been detected through an outlier analysis, for  
32 instance, to identify individuals who systematically replied to the 30 attitudinal questions in a random  
33 inconsistent manner. The inconsistency in the responses to the attitude-elicited questions may be the result of  
34 fatigue and loss of concentration. Indeed, respondents faced the attitudes paragraph of the questionnaire after  
35 the investigation of a possible future vehicle purchase, the SP exercise, the exploration of energy usage and  
36 social network analysis. The complexity and the time spent in these previous parts could have generated  
37 conditions for random responses (Stopher, 2012).

38

39 After data cleaning, the dataset including 90 individuals (9 SP games each, 810 observations to be modelled)  
40 has been used for the frequency analysis and the advanced analysis of the individuals’ attitudes (factor  
41 analysis and cluster analysis). Notably, the percentage of imputed information also decreased to 4% for the  
42 90 respondents considered in the analysis; this small rate of missing data (below 5%) is considered to be

1 inconsequential (Schafer, 1999) and not to affect the statistical analyses as these are likely to be biased when  
 2 the rate is above 10% (Bennett, 2001). The socioeconomic characteristics of these 90 co-workers are shown  
 3 in the diagrams in Table 2.

4  
 5 *Table 2: Frequency analysis*

Variable	Classes	Percentage
<i>Age</i>	Under 20	0%
	20 to 29	14%
	30 to 39	18%
	40 to 49	27%
	50 to 59	27%
	60 to 69	4%
	70 to older	0%
<i>Income</i>	Less than \$20000	0%
	\$20000 to \$34999	8%
	\$35000 to \$49999	22%
	\$50000 to \$64999	15%
	\$65000 to \$79999	16%
	\$80000 to \$104999	20%
	Greater than \$105000	9%
<i>Education</i>	School/college	25%
	1st degree	27%
	Higher degree	38%
<i>Occupation</i>	Administration	9%
	Engineer	17%
	Scientist	47%
	Other	17%
<i>Marital status</i>	Partner	69%
	Single	21%
<i>Gender</i>	Male	62%
	Female	38%
<i>Parking space</i>	No	9%
	Si	81%
		<b>Mean</b>
<i>Number of cars in the household</i>		1.96
<i>Number of persons in the household</i>		2.98

6  
 7  
 8 *4.2 Social Network analysis*

9  
 10 Social connections within the workplace were identified by asking the respondent to name a list of  
 11 colleagues; a “colleague” is defined as “a person at your workplace with whom you commonly interact”. The  
 12 survey then provided a searchable database of the other 500 employees, which the respondent could select  
 13 from and add to their list of colleagues. 88% of respondents who fully completed the questionnaire named at  
 14 least one colleague. On average, 3 to 4 colleagues were named by each respondent.

15  
 16 The social connection section of the questionnaire was carried out to capture information about each  
 17 respondent’s workplace-based social network. For each colleague named, respondents had to state the type  
 18 of relationship using categories of increasing social proximity from: stranger, casual acquaintance, somewhat  
 19 close, very close. The information on the social proximity enables to build an interaction matrix  $W$ , which is  
 20 characterised by a weight on each link to account for the type of relationship between the individuals in the  
 21 models. The weights match values from 0 to 3, 0 when the named colleague is stranger, 3 when the colleague

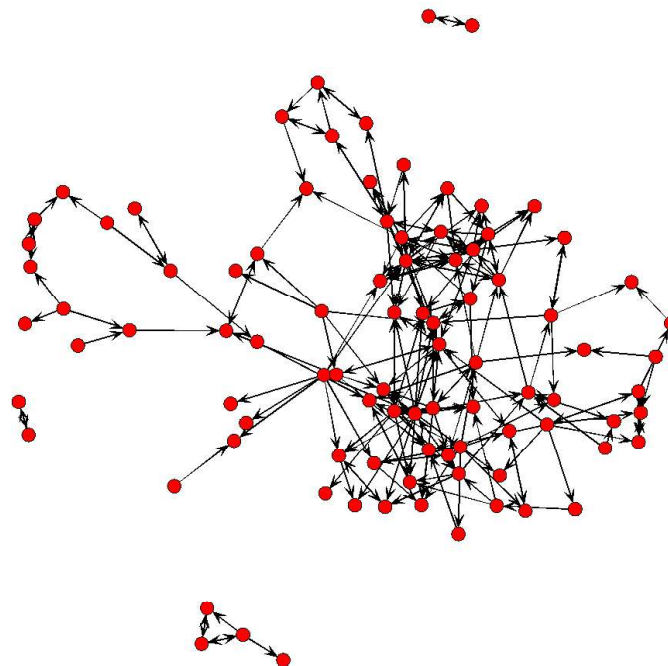
1 is considered very close. Considering this weights' categorisation, a person who only names strangers and, at  
 2 the same time, is not named or named by others as a stranger is assumed to be 'isolated' and does not belong  
 3 to any individuals' social network.

4  
 5 Figure 4 is a graphical representation of the final interaction matrix which includes 76 individuals (i.e. 684  
 6 observations used for the estimations) who are 'non-isolated' since they at least named a colleague as an  
 7 acquaintance and/or were at least named by a colleague as an acquaintance.

8  
 9 As said above, in this specific empirical context, not all the 500 staff members were involved in the data  
 10 collection. However, on average, 70% of the colleagues, who were named by each respondent as at least  
 11 'casual acquaintance' and with occasional interactions were also interviewed. This percentage is up to 84%  
 12 for named colleagues that are at least 'somewhat close'. The resulting social network has all the information  
 13 needed to build the *IPA* variable as precisely as possible for this sample. In other words, the other colleagues  
 14 who were not interviewed were also not named by the respondents and therefore do not belong to the  
 15 immediate social network of those respondents. Therefore, the colleagues who could not be interviewed are  
 16 equivalent to the "world in general", and are not expected to generate bias.

17  
 18 Since the data was collected in 2011, the communication methods might look different if the study were  
 19 replicated today (i.e. the use of social media and instant messages has been sharply increasing). However, the  
 20 fundamental processes of social influence tend to be more durable. In this paper, the focus is not on how  
 21 individuals interact but, rather, on the effect of the social influence generated within a social network where  
 22 individuals influence each other in the everyday life no matter the type of communication mean (face-to-  
 23 face, phone, social media, etc).

24  
 25 *Figure 4: Social Network in the workplace*



26  
 27  
 28 *4.3 Exploratory Factor Analysis and Cluster Analysis to identify individuals'*  
 29 *attitudes*

30  
 31 To define the peers' attitudes which can influence an individual, an exploratory factor analysis (EFA) of the  
 32 attitudinal statements in the survey was conducted on the 90 individuals included in the final cleaned dataset.  
 33 As described above, the survey contained questions designed to understand the respondent's attitudes to  
 34 lifestyle practices, lifestyle openness of liminality and environmental interest.

The reliability of the dataset has been evaluated to correctly apply the exploratory factor analysis. As explained by Fabrigar et al. (1999), it is necessary to check the internal consistency and the sampling adequacy (see Table 3). The analysis of the 16 items considered showed that the determinant of the correlation matrix is much greater than the threshold guaranteeing the absence of multicollinearity (Prato et al., 2005). The Kaiser-Meier-Olkin measure ( $KMO = 0.70$ ) indicates a good level of sampling adequacy (Kaiser, 1974). Finally, the very small p-value evaluated for the Bartlett's test of sphericity means that the null hypothesis of the identity matrix can be rejected (Bartlett, 1951).

Table 3: Indexes of internal consistency and sample adequacy

Index	Acceptance Threshold	Value
Test of multicollinearity	det > 0.00001	0.04
KMO sampling adequacy	KMO > 0.5	0.70
Bartlett's test	p < 0.001	$1.78 \cdot 10^{-14}$

The EFA was conducted by extracting the three factors with Principal Axis factoring and rotating them with Varimax orthogonal rotation to make simpler the association among items of each factor. By looking at the statements with similar factor loadings (a cut-off of 0.43 was chosen to retain important statements and avoid overlapping of the same statement for different factors) and exploring their semantics, the factors explain three different main tendencies of the individual personality: *ecologically and environmentally concerned*, *open to innovation*, *free time lover*. The complete list of statements and factor loadings is presented in Table 4.

The Cronbach's  $\alpha$  was also calculated for each factor to check the internal consistency of the factor in the perception of individual responses (Gliem & Gliem, 2003). The  $\alpha$  was calculated only for the high loading items for each of the three factors:  $\alpha^{ecol} = 0.7$ ,  $\alpha^{innov} = 0.54$ ,  $\alpha^{free} = 0.57$ . All the values were above the acceptance threshold ( $\alpha > 0.50$ )<sup>3</sup> although  $\alpha^{innov}$  and  $\alpha^{free}$  are not particularly high. Nonetheless, confirmatory factor analysis was, in essence, performed when including the high loading items as indicators in the measurement model component of the HCM, as part of the latent variable model structure. The results of the measurement model component were therefore also checked to confirm the accuracy of the item selection.

Table 4: Factor Loadings

	ITEMS	Ecologically and environmentally concerned [ecol]	Open to innovation [innov]	Free time lover [free]
I1	Often you engage in developing your career	0.04	0.36	0.01
I2	Often you engage in playing sports, recreation or exercise.	0.24	0.22	0.01
<b>I3</b>	<b>Often you engage in discussing or researching automobiles.</b>	-0.08	<b>0.59</b>	0.08
<b>I4</b>	<b>Often you engage in helping the environment.</b>	-0.02	<b>0.52</b>	0.02
<b>I5</b>	<b>I often try new activities.</b>	0.12	<b>0.44</b>	0.41
<b>I6</b>	<b>My responsibilities rarely keep me from trying new things.</b>	0.04	0.15	<b>0.61</b>
I7	I have many different groups of friends.	-0.05	0.39	0.14
<b>I8</b>	<b>I often make new friends.</b>	0.2	<b>0.43</b>	0.21
<b>I9</b>	<b>I have plenty of free time.</b>	-0.27	0.38	<b>0.51</b>
<b>I10</b>	<b>Level of agreement: when humans interfere with nature, it often produces disastrous consequences.</b>	<b>0.72</b>	0.06	-0.04
<b>I11</b>	<b>Level of agreement: the balance of nature is very delicate and easily upset</b>	<b>0.68</b>	0.19	0.21
<b>I12</b>	<b>Level of agreement: humans are severely abusing the environment</b>	<b>0.68</b>	-0.19	0.02
I13	Level of agreement: humans have the right to modify the natural environment to suit their needs	0.34	-0.06	0.08
<b>I14</b>	<b>Level of agreement: if things continue on their present course, we will soon experience a major ecological catastrophe</b>	<b>0.47</b>	0.11	-0.02
<b>I15</b>	<b>Level of agreement: plants and animals have as much right as humans to exist</b>	0.24	0.03	0.36
<b>I16</b>	<b>Level of agreement: humans were meant to rule over the rest of nature</b>	0.40	-0.25	0.32

<sup>3</sup> The  $\alpha$ 's cut-off points are much debated in practice. As shown by some influential papers and manuals such as Gliem & Gliem (2003) and (Mallery & George, 2003), the cut-off points can be specified as follows:  $\geq 0.90$  excellent reliability;  $0.70 \div 0.90$  high reliability;  $0.50 \div 0.70$  moderate reliability;  $\leq 0.50$  low reliability.

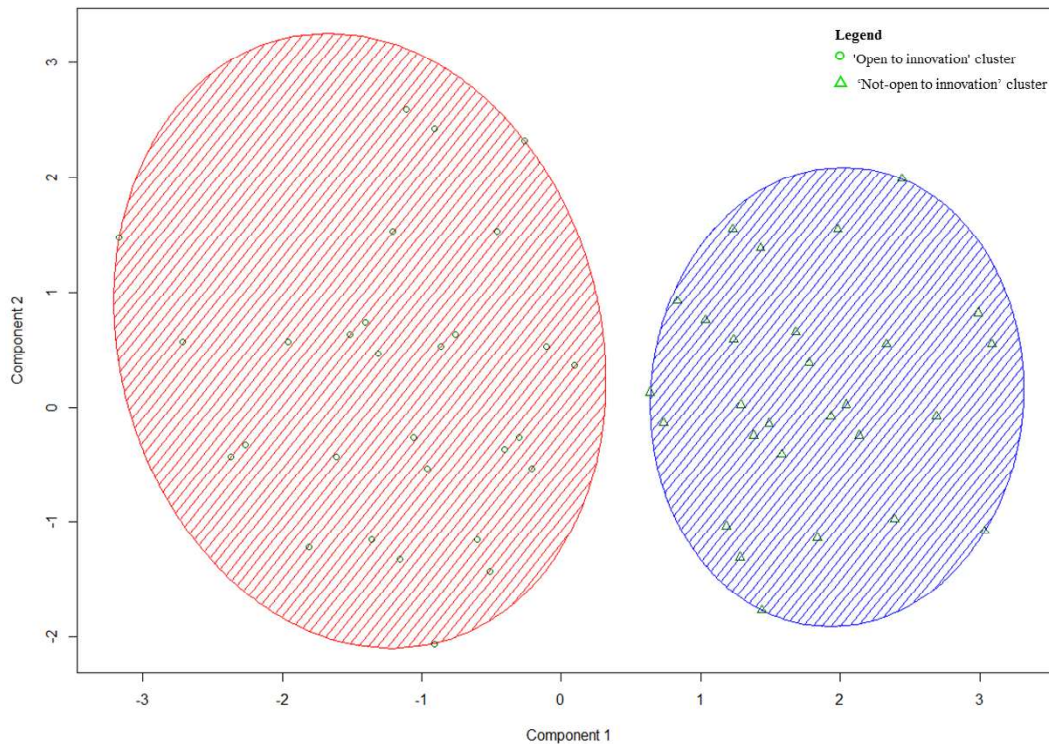
1 Among the factors identified with the EFA, for the following analyses, we employed the attitudinal factor  
 2 'open to innovation', which guaranties significant results during the HCM estimations.  
 3

4 The 'open to innovation' factor is defined by the following items (or indicators); two are part of the lifestyle  
 5 practices construct and the other two are part of lifestyle openness (liminality). The resulting latent factor  
 6 reflects individual attitudes towards new technologies, new friends and the environment. This is, therefore, a  
 7 curious and active person who:  
 8

- 9 I3. often engages in discussing or researching automobiles (indicator 1) *lifestyle practices*
- 10 I4. often engages in helping the environment (indicator 2) *lifestyle practices*
- 11 I5. often tries new activities (indicator 3) *lifestyle openness or liminality*
- 12 I8. often makes new friends (indicator 4) *lifestyle openness or liminality*
- 13

14 Once the 'open to innovation' factor was identified, we chose to cluster and classify individuals in the social  
 15 network using the psychometric attitudinal information from the EFA, rather than using the factor scores as a  
 16 continuous variable. One of the main reasons for taking this approach is the fact that the clustered groups are  
 17 easier to interpret and understand than the factor scores would be. Indeed, the power of the cluster analysis is  
 18 that it enables us to discern homogenous groups with respect to their openness to innovation. The four  
 19 disaggregated statements (two from lifestyle practices and two lifestyle openness to liminality) embodying  
 20 this latent construct have been clustered on the base of their scale response at the sample level. The non-  
 21 hierarchical *k*-mean cluster analysis has been able to classify the survey respondents in two groups as  
 22 revealed by the final cluster centres (Table 3 and Table 7): the *group of people with high scale response* to  
 23 these four specific statements and the *group of people with low scale response*. These groups are also  
 24 graphically represented in Figure 5 with a bivariate cluster plot by using principal components (Pison et al.,  
 25 1999).  
 26  
 27  
 28

Figure 5: Bivariate cluster plot of 'Open to innovation' and 'Not-open to innovation' contacts



29  
 30  
 31  
 32  
 33  
 34  
 35



Table 5: Final cluster centres

	<i>Cluster</i>	
	<i>1</i> <i>(Not open to innovation)</i>	<i>2</i> <i>(Open to innovation)</i>
<i>I12</i>	3	4
<i>I14</i>	3	4
<i>I17</i>	3	4
<i>I21</i>	3	4

Table 6: ANOVA

	<i>Cluster</i>		<i>Error</i>		<i>F</i>	<i>Sig.</i>
	<i>Mean square</i>	<i>df</i>	<i>Mean Square</i>	<i>df</i>		
<i>I12</i>	4.832	1	.433	88	11.171	.001
<i>I14</i>	6.303	1	.531	88	11.881	.001
<i>I17</i>	16.291	1	.501	88	32.501	.000
<i>I21</i>	41.612	1	.415	88	100.356	.000

Table 7: Number of cases in each cluster

<i>Cluster</i>	<i>1</i>	35
	<i>2</i>	55
<i>Valid</i>		90
<i>Missing</i>		0

The large and significant values of the F-test from the ANOVA (Table 6) show that the four statements are all highly contributing to the clustering. As shown by the output, the calculation of the F-test results from the maximization of variation among different clusters, consequently minimising the variation within groups and making the F-value large. Therefore, the F-test cannot be used to evaluate the classical null hypothesis that cluster means are equal but, instead, gives a valuable indication of the cluster solution accomplishment and the role of each variable in this accomplishment (Rogerson, 2014).

#### 4.4 Model results

Table 8 reports the estimation results for three model specifications. Specification 0 does not include the social influence variable. Specifications 1, 2 and 3 have been defined in section 3.3.

Several combinations of variables were tested as part of this study to produce consistent and robust results that can be evaluated and compared. The presented final models all include in the specification of the choice model component the attributes of the alternatives, i.e. price, percentage difference in acceleration between EV and conventional car, range and logarithm of recharging time/refuelling time. The serial correlation effect has always been included in the model to take into account the correlation among the responses of the same individual. All the socioeconomic variables (Age, Gender, Number of cars per household, Number of people in the household, Occupation, Level of education and Marital status) have been tested in both the choice model component and the structural model component to measure their linear-effect. Indeed, as in the choice model component, the structural model component includes socioeconomic variables to explain the characteristics of the respondents in relation to the analyses of the latent variable. However, in the results section, we only present the model with significant results.

1 To evaluate their non-linear effect, the attributes of the alternatives have been interacted with some  
 2 socioeconomic variables, such as income classes, age classes, gender, number of people per household,  
 3 profession, education, purpose of purchase (which takes the value 1 if a person wanted to replace the old car,  
 4 0 if he/she wanted to have an additional one), possibility to plug-in (where 'possibility to plug-in' takes the  
 5 value 1 if the person had seen a recharge station near familiar places such as workplace, supermarket,  
 6 restaurant, gym), and participation in an electric vehicle project at the workplace (where EV Project  
 7 participation takes the value 1 if a person had previously participated in the EV project).

8  
 9 Among the wide range of interactions between attributes of the alternative and socio-economic variables  
 10 which were estimated, the presented models, which show statistically significant results in terms of the  
 11 parameter (t-test) and goodness of fit, have three interactions (i.e. the product of price and income, the  
 12 product of the log of charging/refuelling time and number of people in the household and the product of the  
 13 log of charging/refuelling time and the possibility to plug-in).

14  
 15 Overall, the coefficients of the alternative attributes included in the choice model component have always the  
 16 correct sign and are significantly different from zero at least at a 95% confidence level. As expected, price  
 17 and logarithm of recharging time/refuelling time are negative while electric driving range and percentage  
 18 difference in acceleration between EV and conventional car are positive. Moreover, three interaction  
 19 variables are also significant at more than the 95% confidence level. First, the interaction of price with a  
 20 household income greater than £80k per year is positive suggesting a smaller perception of the price  
 21 disutility for people in these higher income classes. Second, the interaction between log recharging time and  
 22 the 'possibility to plug-in' the EV in familiar places is also positive thus reducing for such individuals the  
 23 disutility of recharging time attribute. Third, the disutility of recharging time is also slightly reduced for  
 24 people who live in households with more than 4 people. This interaction is not very easy to interpret. The  
 25 effect of 'household with more than 4 people' is potentially due to a combination of correlated reasons such  
 26 as higher car ownership (therefore less pressure on recharging time) and larger housing units (therefore the  
 27 security of private home charging). However, the data does not allow these effects to be disentangled as we  
 28 have no information about home charging, and we empirically find that the interaction of recharging time  
 29 with the 'number of cars' variable is not significant whereas the interaction with 'household with more than  
 30 4 people' is very significant. When the latent variable ('*Latent Open to innovation*') is included in the utility  
 31 of the EV, its coefficient is always highly significant at more than 95% confidence and with a positive sign;  
 32 therefore, we infer that an individual characterised by 'openness to innovation' is strongly associated with  
 33 the increased utility of the EV with respect to the conventional car, thus boosts the demand for EV.

34  
 35 The structural component illustrates which socioeconomic variables characterise people with an 'openness to  
 36 innovation'. These individuals are very likely to be younger than 40 years as suggested by the highly  
 37 significant positive coefficient on the dummy variable for age  $\leq 40$ . In Specification 1 and 2, a coefficient  
 38 that is always negative across the model formulations and significant at more than 95% confidence level  
 39 suggests that engineers at this workplace are not inclined to be open to innovation (i.e. they score quite low  
 40 on making new friends, discovering new information about automobiles, trying new activities or helping the  
 41 environment). Moreover, the coefficient of high education (1<sup>st</sup> degree or higher) is always negative and, in  
 42 particular, is significant at 93% confidence level in Specification 1 and 2 suggesting that this class of people  
 43 is also not likely to be open to innovation. While a confidence level between 80% and 94% is usually  
 44 considered a weak effect, given the small size of the dataset and the complexity of the model estimated, the  
 45 statistics are not unreasonable.

46  
 47 In the measurement model, the significant coefficients of the latent variable (for indicators 2, 3 and 4 always  
 48 greater than 95%, for indicator 4 there is a decrease only in Specification 3) confirm the results of the  
 49 exploratory factor analysis and the presence of correlation among the indicators and the latent variable  
 50 construct.

51  
 52 We now examine in detail the results in light of the different specifications used for the inclusion of the IPA  
 53 variable. In Specification 1, the IPA coefficient is positive, indicating that the peers' attitude of being open to  
 54 innovation tends to increase the utility of purchasing an EV, but this is not very significant, at 85%  
 55 confidence level, which does not confirm H1. The dummy formulation of the social influence variable has  
 56 also been tested and found to be even less significant. The significance of the effect of the IPA variable is

1 instead very large in Specification 2, i.e. IPA has a significant positive effect on the '*openness to innovation*'  
2 attitude of the survey respondent, at more than 95% confidence level, which confirms H2. Therefore, the  
3 'open to innovation' attitude of the individual is strongly related with the 'open to innovation' attitude of  
4 his/her peers; this indirectly influences the perception of EV utility through the effect of the latent variable  
5 included in the choice model component. Finally, looking at the results of Specification 3, the latent variable  
6 does not seem to be manifested by the IPA variable used as an indicator (see "Coefficient indicator IPA"), as  
7 it is only significant at 27% confidence level, which does not confirm H3. The combined inclusion of IPA in  
8 both the choice model component and the structural model component does not produce any significant  
9 results.

10  
11 Using the LR statistic to compare Specification 0 with Specification 1 and Specification 2, as displayed in  
12 Table 9, both models, with IPA variable in the choice model and the structural model component, are  
13 significantly different from their restricted versions (model without IPA) at more than the 95% confidence  
14 level. Confirming that the inclusion of IPA variable increases the goodness of fit of the original model.  $AIC_c$   
15 is finally performed to be able to compare Specification 1, Specification 2 and Specification 3, which are  
16 non-nested formulations. The lowest value of  $AIC_c$  suggests that in terms of goodness-of-fit the Specification  
17 2 is the best model formulation while the inclusion of the social influence variable as an indicator in  
18 Specification 3 does not add significant value to the statistical fit of the model. This is not surprising also  
19 considering the t-tests obtained for the measurement model component of Specification 3.

20  
21 According to the statistical tests performed, Specification 2 is the best model to represent the phenomenon.  
22 This means that, in this specific context, the social influence generated by peers' attitudes of openness to  
23 innovation is indirectly related to the individual's choice. Indeed, accounting for peers' *open to innovation*  
24 attitudes does not seem to directly affect the utility of the electric vehicle by explaining any part of its  
25 systematic heterogeneity (H1) nor to help identify how the latent variable is manifested as an indicator of the  
26 social influence (H3). Instead, peers' *open to innovation* attitudes are positively and significantly related to  
27 the tendency of an individual to be also 'open to innovation' (H2). Therefore, the IPA *open to innovation* in  
28 Specification 2 suggests that an individual characterised by an 'open to innovation' attitude is inclined to be  
29 part of a social network with peers having that specific attitude.

1

Table 8: Model results

Variable Names	Specification 0			Specification 1			Specification 2			Specification 3		
	Value	Robust t-test		Value	Robust t-test		Value	Robust t-test		Value	Robust t-test	
<i>Choice Model Component</i>												
ASC (EV) <sup>‡</sup>	-21.50	-1.40	*	-15.80	-1.27	*	-17.40	-1.15		-22.40	-1.33	*
Difference % in acceleration (EV)	7.15	4.20	***	7.08	4.37	***	7.08	4.36	***	7.12	4.18	***
Range [100 miles]	2.00	3.05	***	1.98	2.94	***	1.98	2.94	***	1.99	3.03	***
Price [£ 1000]	-5.15	-2.73	***	-5.02	-2.69	***	-5.04	-2.66	***	-4.90	-2.54	***
» * Income >= £80000	5.02	2.13	***	4.64	1.99	***	4.72	2.01	***	4.66	1.92	**
Log of charging - refuelling time	-3.53	-6.01	***	-3.87	-4.61	***	-3.83	-4.22	***	-3.45	-5.75	***
» * N. people/household > 4 pers (EV)	0.96	2.29	***	1.08	2.48	***	1.02	2.38	***	0.99	2.14	***
» * Possibility to plug in (EV)	2.13	4.02	***	2.46	3.11	***	2.44	2.84	***	2.05	3.82	***
Purpose of purchase (EV)	-1.76	-1.21		-2.12	-1.49	*	-2.04	-1.38	*			
IPA Open to innovation (EV)				0.22	1.44	*						
Latent Open to innovation (EV)	9.91	2.41	***	8.47	2.71	***	9.10	2.35	***	9.67	2.12	***
Serial correlation (EV)	-0.16	-3.66	***	0.28	5.40	***	0.26	4.43	***	-0.16	-2.81	***
<i>Structural Model Component</i>												
Age <= 40 years old	0.33	2.36	***	0.40	3.01	***	0.38	2.76	***	0.34	2.14	***
Occupation – Engineer	-0.33	-1.94	**	-0.42	-2.50	***	-0.41	-2.32	***	-0.31	-1.39	*
Occupation – Scientist										0.01	0.13	
High education – 1 <sup>st</sup> degree or higher	-0.16	-1.28	*	-0.27	-1.80	**	-0.26	-1.81	**	-0.18	-1.15	
EV Project participation	0.13	1.40	*	0.15	1.40	*	0.15	1.54	*	0.11	1.11	
IPA Open to innovation							0.03	2.46	***			
LV Constant	3.70	36.59	***	3.76	31.09	***	3.67	32.12	***	3.70	29.94	***
LV $\gamma$	-1.40	-5.66	***	-2.53	-5.12	***	-2.62	-4.05	***	-1.42	-5.27	***
<i>Measurement Model Component</i>												
Intercept indicator 2 (I4)	0.70	0.67		1.16	1.19		0.85	0.84		0.75	0.63	
Intercept indicator 3 (I5)	0.65	0.47		0.96	0.77		0.69	0.53		0.67	0.46	
Intercept indicator 4 (I8)	1.34	1.20		1.77	1.84	**	1.13	1.00		1.39	1.04	
Intercept indicator IPA										1.89	2.16	***
Coefficient indicator 2 (I4)	0.85	2.96	***	0.72	2.68	***	0.81	2.93	***	0.84	2.57	***
Coefficient indicator 3 (I5)	0.79	2.14	***	0.71	2.09	***	0.78	2.23	***	0.79	2.00	***
Coefficient indicator 4 (I8)	0.66	2.21	***	0.54	2.10	***	0.72	2.41	***	0.65	1.82	**
Coefficient indicator IPA										-0.08	-0.34	
Standard deviation indicator 1 (I3)	-0.53	-4.93	***	-0.56	-5.21	***	-0.53	-5.23	***	-0.52	-4.59	***
Standard deviation indicator 2 (I4)	-0.29	-3.58	***	-0.29	-3.48	***	-0.29	-3.66	***	-0.29	-3.56	***
Standard deviation indicator 3 (I5)	-0.20	-2.75	***	-0.20	-2.77	***	-0.20	-2.80	***	-0.20	-2.75	***
Standard deviation indicator 4 (I8)	-0.10	-1.20		-0.09	-1.11		-0.11	-1.30	*	-0.10	-1.20	
Standard deviation indicator IPA										-0.71	-29.90	***
<i>N.param.</i>		27			28			28			30	
<i>N.obs.</i>		684			684			684			684	
<i>N.draws</i>		2000			2000			2000			2000	
<i>Final LL over choices</i>		-469.07			-466.59			-466.41			-523.46	

2  
3 \*\*\* p-value smaller or equal 5%; \*\* p-value between 5% and 10%; \* p-value between 10% and 20%  
4 <sup>‡</sup> (EV) indicates that the variable is only included in the utility function of EV

Table 9: Models comparison

Compared		Test	
Model	Restricted	LR statistic	p-value
<i>Specification 1</i>	<i>Specification 0</i>	4.94	0.03
<i>Specification 2</i>	<i>Specification 0</i>	5.30	0.02

Model	AIC <sub>c</sub> Value
<i>Specification 0</i>	994
<i>Specification 1</i>	992
<i>Specification 2</i>	991
<i>Specification 3</i>	1110

## 5. Discussion & Conclusions

This paper proposes a new analytical framework to measure the effects of peers' attitudes on the decision making process of the individual. Indeed, while previous papers focused their attention on capturing conformity to a certain real or hypothetical choice, we investigate the subtle effect of attitudes that underlies this choice. The suggested measure, the individual's peer attitude (IPA) variable, is defined as the attitudes of peers in a social network. It enables us to model the correlated environmental effects that might indirectly affect the individual's choice. This measure combines detailed information, collected through Axsen and Kurani's (Axsen & Kurani, 2011) multi-method research instruments, regarding the attitudes in the individual's social network and the social proximity of the individuals in the social network. Nonetheless, the proposed methodology is generalisable for different types of attitudes and different types of tie strengths when considering different contexts.

The analytical approach was tested in the specific case of EV purchase preferences in a workplace. The dataset collected for this context offers several essential information on a) choices regarding the possible purchase of such vehicle collected with a classic stated preference survey, b) different descriptors of social influence such as the number of the individuals and their relationships in the social network, thus, information on the tie strength as described by Carrasco et al. (2008) and Axsen & Kurani (2011), and c) several psychometric indicators on sociological constructs (Axsen et al., 2013) that can underline latent attitudes of the individuals.

We devised a method that enabled us to investigate how peers indirectly influence an individual's choice behaviour but also allowed us to minimise cognitive biases that arise from the indirect elicitation of peers' preferences and attitudes, which has been the common approach to date (Kamargianni et al., 2014). Initially, we investigated the attitudes of the respondents using factor analysis of the psychometric indicators from the survey. Next, with cluster analysis of the attitudinal items and the relationship matrix among co-workers, we identified contacts with that specific attitude in each individual's social network. This variable was the combination of the clusters and the interaction matrix taking into account the social proximity in the individual's social network, the so-called 'individual's peer attitude variable. Among the individual latent constructs identified during this procedure, the 'open to innovation' characteristic produced the most interesting results.

We explored how the peer's attitudes can affect the mechanisms of the decision making process by testing behavioural hypotheses regarding the effects of the IPA variable. The statistical analysis of the models has suggested that the inclusion of IPA variable indirectly affects the decision making process of the individual. Indeed, a person that is open to innovation is likely to be part of a social network in which peers have the same 'open to innovation' attitude (i.e. a positive relationship between IPA variable and the latent variable) and has a greater preference for EVs (i.e. the magnitude of the latent variable increases with a larger IPA variable, which means a larger utility of EV). This finding seems to confirm the presence of correlated effects which refer to a person behaving like the other members of the group to which he/she belongs (e.g. a workplace) as described by Manski (1993).

Our results are not directly comparable with results in the literature as this is the first model to include measures of this type. However, as in our findings, Kamargianni et al. (2014) showed that inclusion of the latent variable 'Parents: walking lovers' to take into account the parents' attitude towards walking improves the goodness of fit for the choice model and positively impacts the children's preference for that travel mode. In the specific case of EV demand analysis, Cherchi (2017) showed that social conformity generated by injunctive norms and included as a latent variable positively affects the EV utility. Moreover, in Kim et al. (2014), in which the EV preference is analysed with HCM, the direct inclusion of the social conformity variable (EV adoption in the social network) in the choice model component does not have a strong impact on the purchase preference confirming our results with Specification 1.

The results also show that the peers' attitude is a significant explanatory variable of an individual's attitude, as shown by the significance of the IPA variable in the structural model of the second HCM specification. This has important methodological implications for the application of HCM to capture social influence impacts on choice behaviour. Typically, when specifying structural models for HCM, analysts almost exclusively use the demographic characteristics of the single individual. On the contrary, our findings show that including measures of attitudes of members of the individual's social network in the structural model considerably increases the model performance. Therefore, our results suggest that, when using HCMs to model attitudinal effects related to the adoption of new transport mode, the attitudinal propensity of peers might significantly affect the magnitude of the latent variable and, indirectly, the utility function of the considered modes. Nonetheless, the fact that a person that is open to innovation is likely to be part of a social network in which peers have the same 'open to innovation' attitude is in line with findings in social simulation research on opinion formation and conformity showing that like-minded individuals with similar attitudes group together in the society (Mäs & Flache, 2013).

### 5.1 Policy implications

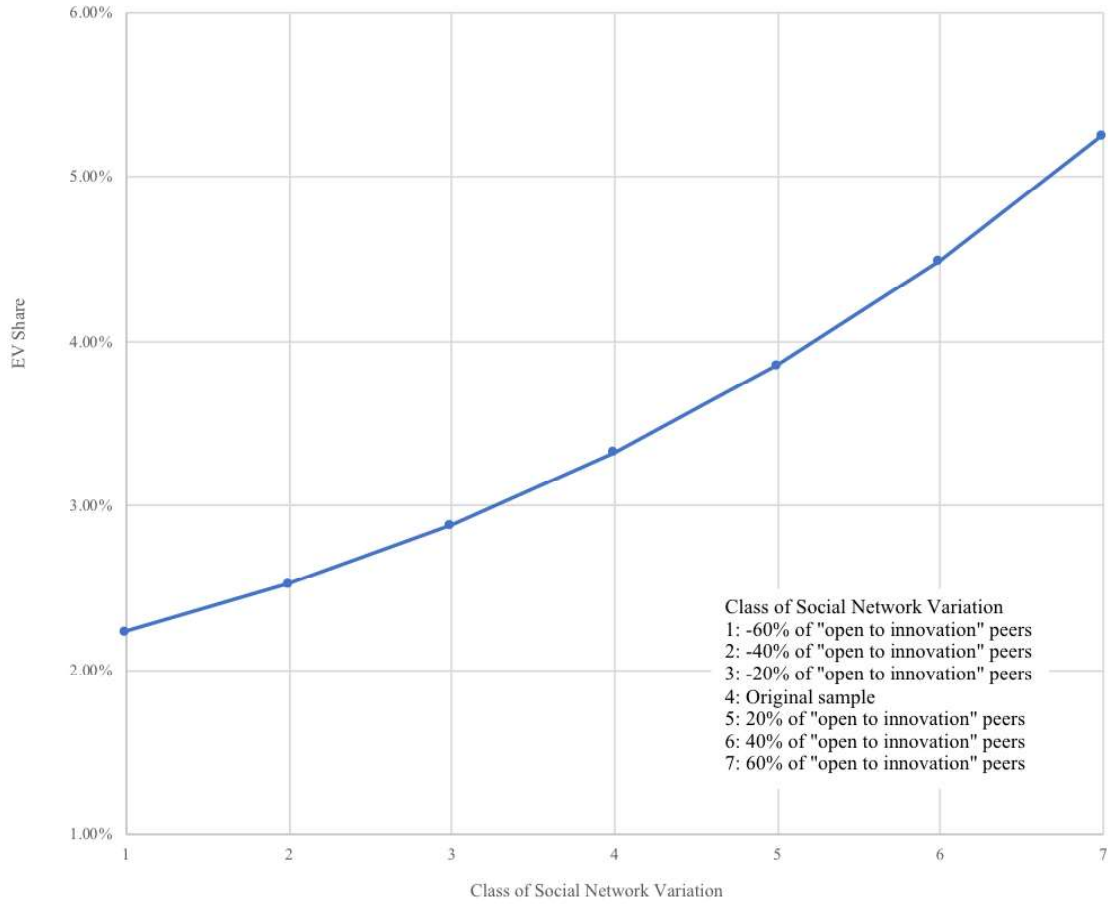
We undertook additional analysis to explore how different levels of the IPA variable can affect the magnitude of the latent 'open to innovation' variable, and therefore the preference between EVs and CVs. This was achieved by computing the overall utility (given by both the choice model component and the structural model) as described in Cherchi (2017). Three scenarios were simulated to test the changes in magnitude of the latent variable and, consequently, the EV preference due to different IPA variable scores:

- Scenario 1 with different percentages of peers that are open to innovation (we tested  $\pm 60\%$ ,  $\pm 40\%$ ,  $\pm 20\%$  of 'open to innovation' peers with respect to the original sample percentage)
- Scenario 2 with different percentages of social proximity in the individual's social network i.e. weight variation (we tested different combinations of percentage, from 55% to 15%, for each social proximity class; e.g. 45% casual acquaintance, 30% somewhat close and 25% close)
- Scenario 3 with different percentages of peers that are open to innovation and different percentages of social proximity in the individual's social network

The sensitivity analyses (Figure 6, Figure 7 and Figure 8) confirm that the increase of the IPA variable positively affects the preference for EV as the probability of choosing EV increases in all the three scenarios. The combination of the variation of percentages of open to innovation peers and the variation of the class of weight affects the EV share the most. In contrast, when these variations are kept separated, the variation of percentages of open to innovation peers seems to be more effective than the variation of the weights. For example, let us consider an increase of 40% in the percentage of open to innovation peers with respect to the original sample (case 7 in Figure 6) and an increase of 43% in the percentage of close friends (case 6 in Figure 7, 55% close friends plus 30% somewhat close). Looking at the two figures, it is possible to see that the former case generates a higher EV share (i.e. = 4.5%) than the latter (i.e. EV share = 4.2%).

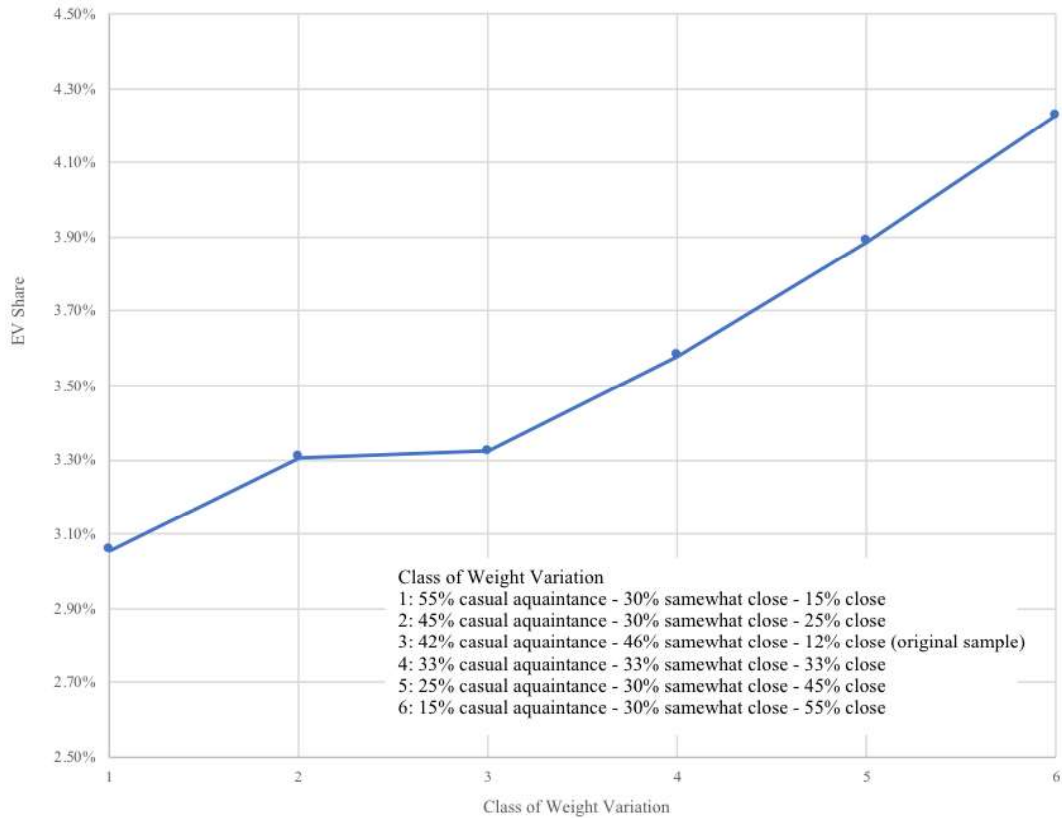
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Figure 6: Sensitivity analysis of IPA variable scores - Social Network Variation



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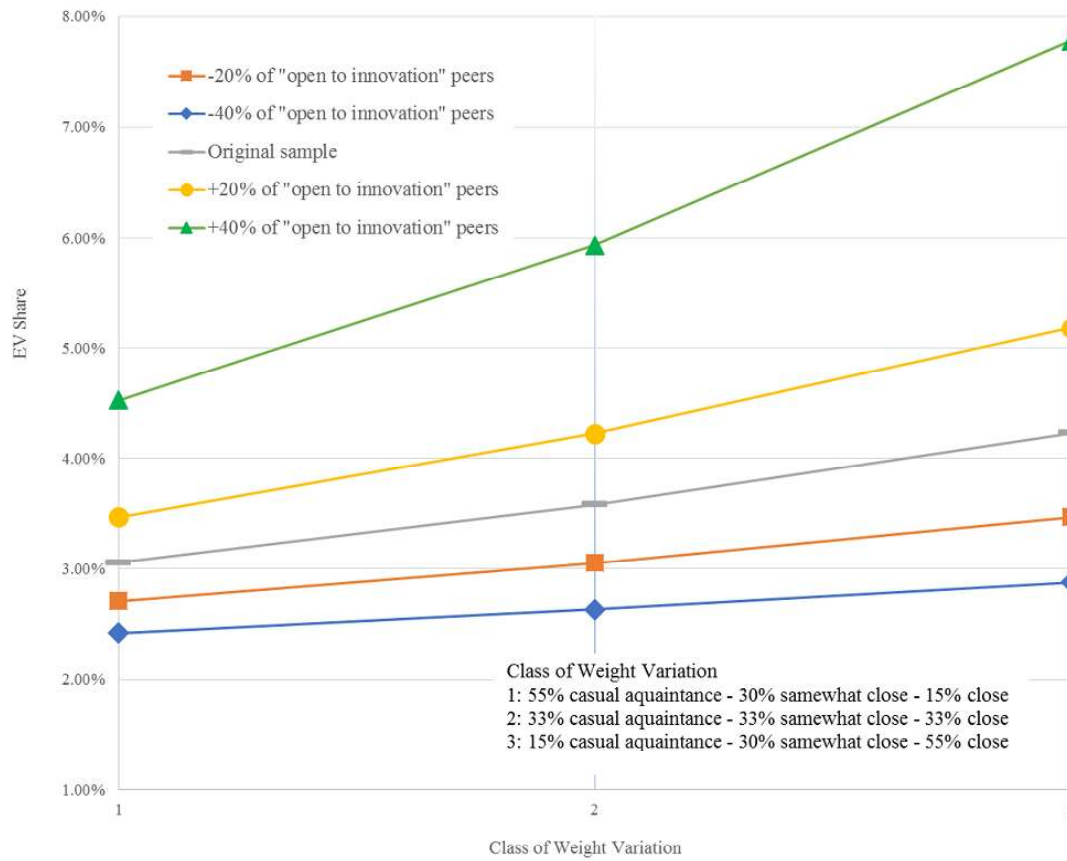
Figure 7: Sensitivity analysis of IPA variable scores - Weight Variation



5  
6

1  
2

Figure 8: Sensitivity analysis of IPA variable scores - Combined Social Network and Weight Variation

3  
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5 Therefore, a large social network, in which like-minded individuals have similar attitudes and a high degree  
 6 of social proximity, can indeed be the target of a strategic policy promoting a new product, technology or  
 7 service and accelerate its adoption. For instance, targeting like-minded individuals in a social network with  
 8 marketing campaigns may facilitate the diffusion of the product. In this case, the diffused information would  
 9 be less subject to scepticism and rejection (Ng, 2001) and, therefore, more easily internalised. This is very  
 10 important considering that the efficacy of a new policy campaign is largely affected by the dissemination of  
 11 the information aimed at increasing awareness (Axsen & Kurani, 2014).

12

13 Finally, there are two substantial reasons for proposing this measure. The first reason is practical; when  
 14 directly enquiring about the attitudes of others, the analyst is forced to ask the individual about his/her  
 15 perception of the peers' attitudes. This is reasonable when asking about one or two contacts in the social  
 16 network, but it becomes very complex when the individual's social network is larger than two as it generally  
 17 happens in reality. The IPA method makes it easier to account for correlated effects generated by the  
 18 attitudes of others in a social network. The second reason is related to the sources of influence that can affect  
 19 the decision-making process when a new technology is in the early stages of adoption. It is widely shown  
 20 that attitudes may affect the intention and subsequently the choice behaviour (Ajzen, 1991), and, as  
 21 illustrated in this work, this can be reinforced when a person that is open to innovation is likely to be part of  
 22 a social network in which peers have the same attitude. On the contrary, previously studied measures of  
 23 other sources of influence might not be appropriate in the context of new technologies. For example,  
 24 measures of conformity based on the choice of others cannot be calculated because there are not many  
 25 people that have made the choice (of the new technology) in the real world. Or it would simply be based on  
 26 hypothetical responses concerning imaginary rates of adoption. The proposed IPA measure can instead  
 27 always be quantified to test the impact of this type of correlated effect on the decision making process of the  
 28 individual.

29

30 An interesting and genuinely novel application of the proposed methodology would, therefore, be to combine  
 31 it with a simulation model of the diffusion of new technologies. Diffusion models such as the Bass model



(Bass, 1969) are generally characterised by simple demand models. Linking a diffusion model with the demand model in this paper could help to better predict the extent of adoption (and therefore diffusion) of the new technology within specific social networks, particularly due to correlated effects occurring within the social networks. This is especially important in the initial segment of penetration of new technology in the presence of few observable innovators and, subsequently, few observable imitators (Jensen et al., 2016).

## 5.2 Limitations and future research

It is remarkable to acknowledge that data collection plays an important role in specifying the IPA variable. In an ideal situation, all the employees of the workplace should have been interviewed to have a precise measure of the information needed. In the present study, the possible bias generated by interviewing only a proportion of employees is minimised by the name generator approach adopted to collect the data. Almost all the colleagues named by each interviewee were also interviewed, thus, resulting in a closed and well defined social network. It is also important to note that the specific findings of this empirical analysis should not be too quickly generalized (e.g. the proportion of respondents that report a particular process of social influence) to a broader population. Nevertheless, the workplace case is not meant to be representative of, say, a target population of UK new vehicle buying households. Instead, the workplace provided a unique opportunity to study processes of social influence in depth.

Another limitation of the study is the inclusion of the influence generated by only one type of actor, the co-worker. As explained previously, this context makes it possible to analyse social influence within a social network which includes “high-tech” in a technology-based workplace, some of who had direct exposure to the technology. However, a larger overview of the individual’s social network that includes family and friends may add a piece of important additional information to the IPA variable, and better explain the heterogeneity in the decision-making process. For example, it would be interesting to analyse the different effects generated by an IPA variable that considers the “high-tech” peers, i.e. co-workers, against those who can be considered to be relatively lower-tech peers, i.e. friends and family.

Furthermore, future studies might consider a variation of the IPA variable formulation by considering a different measure of the tie strength. For instance, instead of using the social proximity, the frequency of interaction or the means of communication (i.e. face-to-face versus instant messages and social media) can be employed as a proxy for the tie strength as they are particularly important in transport and travel behaviour contexts (Calastri et al., 2017; Sadri et al., 2018). Finally, an important step for further research would be the inclusion of specific measures of social interaction and processes of compliance and conformity to analyse and compare these different types of influence. As shown by Pettifor et al. (2017), it is difficult (and sometimes not possible) to isolate and distinguish among the effects of interpersonal communication, neighbourhood effects and social norms. Therefore, the simultaneous inclusion of all these types of social influence can give a better explanation of the heterogeneity and a clearer picture of how social influence might affect the choice of individuals.

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