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

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

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

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

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

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

The rest of this paper is structured as follows. Section 2 briefly summarises the current literature on modelling the effect of social influence on transport choices, highlighting the challenges modern researchers are still facing and presents conceptual framework and hypotheses. Section 3 presents the methodology adopted in this research. Section 4 presents the empirical application and discusses the substantive results, and Section 5 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 work 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[2]), 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.

[2] More specific details on HCM structure can be found in subsection 3.2

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

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

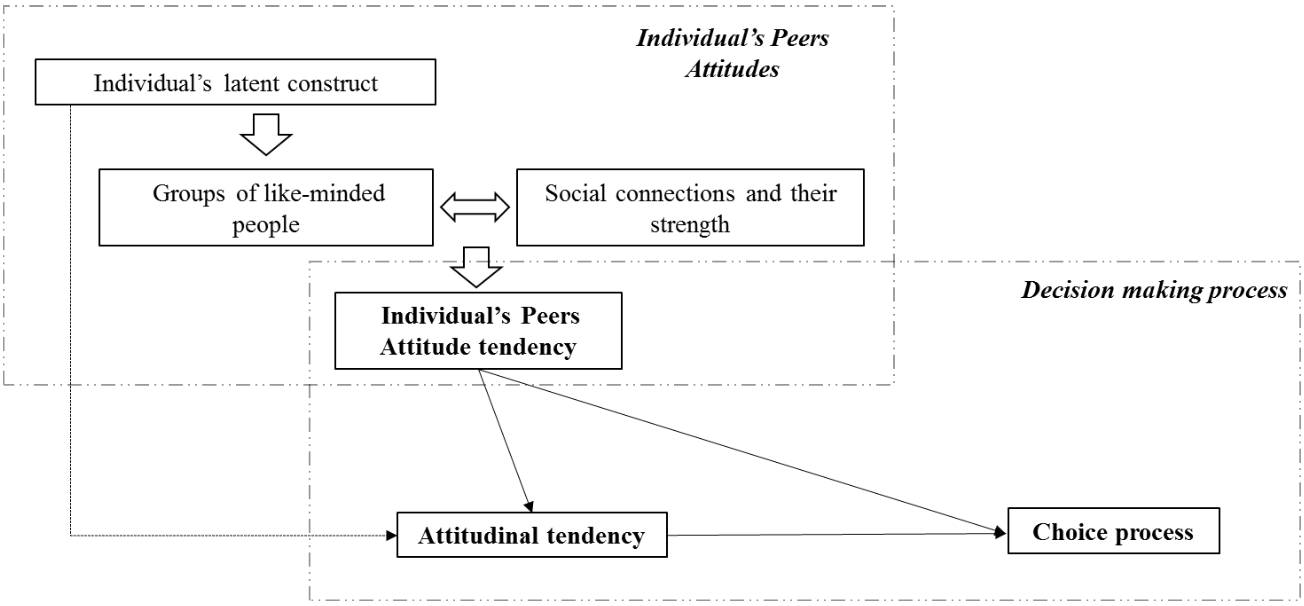
Although there have been significant advancements on measuring the effects of social influence, most of the formulations described above are limited to capturing conformity to a certain choice, without addressing the mechanisms by which attitudes and opinions of others affect one’s choice. None of them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

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

2.1 Conceptual framework

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

Figure 1: Conceptual Framework



As indicated on the top left side of Figure 1, the specification of the IPA variable involves different steps:

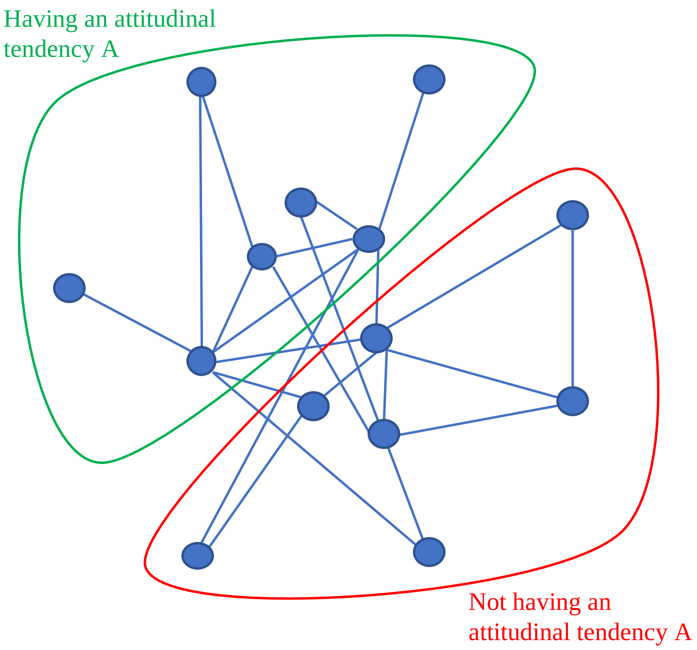
1. To identify the individual's latent constructs, the attitudinal latent constructs of the respondents are investigated using factor analysis of psychometric indicators.

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.).

3. Moreover, social connection and their strength within the social network are identified with the help of the interaction matrix.

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).

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



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

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

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

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

3. Modelling methodology

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

3.1 IPA variable specification

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

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

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

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

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

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

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

With the help of the interaction matrix, two types of variables have been specified and tested in the model: in its continuous form, the IPA_i can be defined as a weighted sum of the number of *m* peers (within a social network of individual *i*) who fall into a cluster characterised by certain attitudinal tendencies A (Eq 3); IPA_i^d is the dummy variable to take into consideration of a maximum value above a certain limit (Eq 4), such as 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 in the network as described above.

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

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

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

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

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

3.2 Incorporation of the social influence variable in a choice model

The variables specified in the above subsection (Eq 3 and Eq 4) have been incorporated in the equations of following subsection (Eq 5, Eq 6 and Eq 7) to investigate the research objective by extending the HCM 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 important 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:

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

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), β_{aX}, β_{aS} and β_{aAtt} are the respective vectors of parameters to be estimated, ASC_a is the alternative-specific constant. The error term ε_{air} is assumed to be identically and independently distributed extreme value type 1 (EV1), while the noise η_{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*:

$$Att_i = c + \delta S_i' + \eta_{ai} + \gamma_i \tag{6}$$

where δ is the vector of parameters associated with the socioeconomic characteristics, *c* is the intercept and γ_i is the error term assumed to be normally distributed $N(0, \sigma_\gamma)$. η_{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}:

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

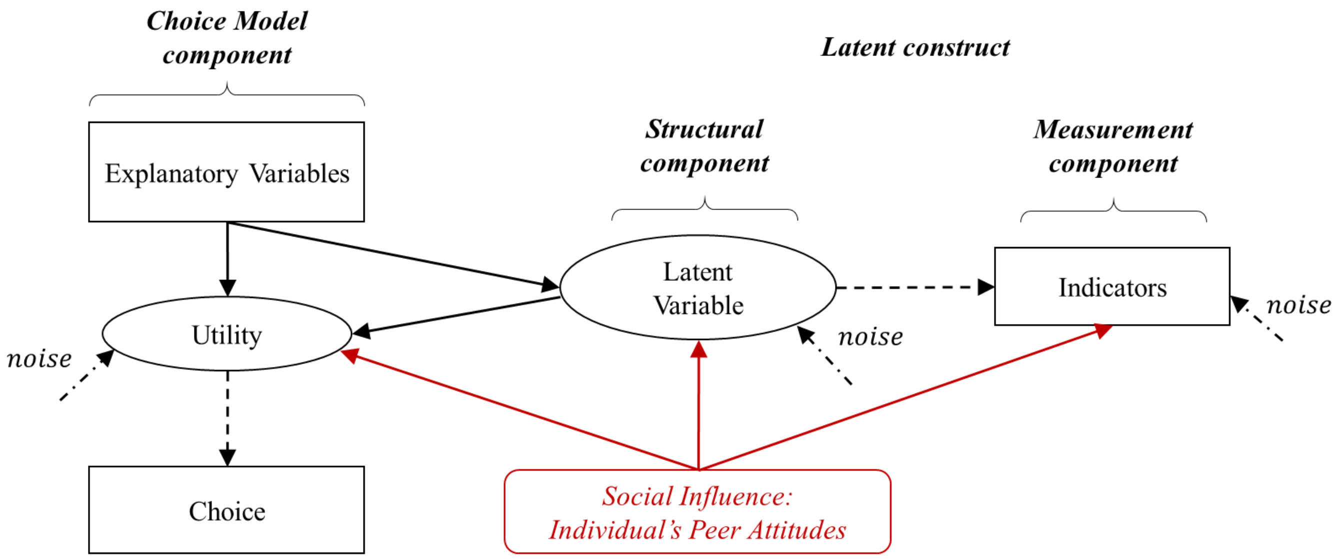
where θ_f is the coefficient characterising the latent variable, d_f is the intercept and μ_{fi} is the error term assumed to be normally distributed $N(0, \sigma_\mu)$.To be able to identify the mathematical problem, for the first indicator, d_f is set equal to 0 and θ_f is set equal to 1, following 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, $g_{I_f}\left(I_{fi} \middle| Att_i(\gamma_i)\right)$, all integrated over the distribution of η_i and γ_i (Jensen et al., 2013):

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

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

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



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

In Formulation1, the variable has been included in the choice model component to test the first hypothesis (H1):

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

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

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

Finally, with the inclusion of the social influence variable as an additional "indirect" indicator in the measurement model component (Formulation 3), we can explore the third hypothesis (H3):

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

$$Att_i = c + \delta S_i^{'} + \eta_{ai} + \gamma_i \tag{11}$$

$$I_{fi} = d_f + \theta_f Att_i + \mu_{fi}$$
$$\boldsymbol{IPA_i^d} = d_{IPA} + \theta_{IPA}Att_i + \mu_{IPAi}$$

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 & Fetiarison, 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).

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

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

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

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

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

After data cleaning, the dataset including 90 individuals (9 SP games each) has been used for the frequency analysis and the advanced analysis of the individuals' attitudes (factor analysis and cluster analysis). Notably, the percentage of imputed information also decreased to 4% for the 90 respondents considered in the analysis; this small rate of missing data (below 5%) is considered to be inconsequential (Schafer, 1999) and not to affect the statistical analyses as these are likely to be biased when the rate is above 10% (Bennett, 2001). The socioeconomic characteristics of these 90 co-workers are shown in the diagrams in Table 2.

Table 2: Frequency analysis

Variable	Classes	Percentage
Age	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%
Income	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%
Education	School/college	25%
	1st degree	27%
	Higher degree	38%
Occupation	Administration	9%
	Engineer	17%
	Scientist	47%
	Other	17%
Marital status	Partner	69%
	Single	21%
Gender	Male	62%
	Female	38%
Parking space	No	9%
	Si	81%
		Mean
Number of cars in the household		1.96
Number of persons in the household		2.98

4.2 Social Network analysis

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

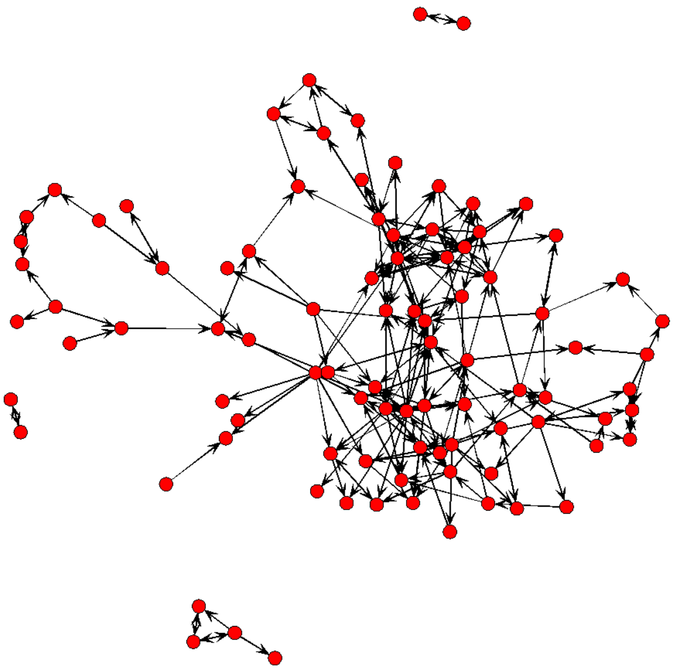
The social connection section of the questionnaire was carried out to capture information about each respondent’s workplace-based social network. For each colleague named, respondents had to state the type of relationship using categories of increasing social proximity from: stranger, casual acquaintance, somewhat close, very close. The information on the social proximity enables to build an interaction matrix W, which is characterised by a weight on each link to account for the type of relationship between the individuals in the models. The weights match values from 0 to 3, 0 when the named colleague is stranger, 3 when the colleague is considered very close. Considering this weights’ categorisation, a person who only names strangers and, at the same time, is not named or named by others as a stranger is assumed to be ‘isolated’ and does not belong to any individuals’ social network.

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

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

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

Figure 4: Social Network in the workplace



4.3 Exploratory Factor Analysis and Cluster Analysis to identify individuals’ attitudes

To define the peers’ attitudes which can influence an individual, an exploratory factor analysis (EFA) of the attitudinal statements in the survey was conducted on the 90 individuals included in the final cleaned dataset. As described above, the survey contained questions designed to understand the respondent’s attitudes to 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	$1.78*10^{-14}$

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 α was also calculated for each factor to check the internal consistency of the factor in the perception of individual responses (Gliem & Gliem, 2003). The α 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 (α > 0.50)[3] although α^{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
I3	**Often you engage in discussing or researching automobiles.**	-0.08	**0.59**	0.08
I4	**Often you engage in helping the environment.**	-0.02	**0.52**	0.02
I5	**I often try new activities.**	0.12	**0.44**	0.41
I6	**My responsibilities rarely keep me from trying new things.**	0.04	0.15	**0.61**
I7	I have many different groups of friends.	-0.05	0.39	0.14
I8	**I often make new friends.**	0.2	**0.43**	0.21
I9	**I have plenty of free time.**	-0.27	0.38	**0.51**
I10	**Level of agreement: when humans interfere with nature, it often produces disastrous consequences.**	**0.72**	0.06	-0.04
I11	**Level of agreement: the balance of nature is very delicate and easily upset.**	**0.68**	0.19	0.21
I12	**Level of agreement: humans are severely abusing the environment.**	**0.68**	-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
I14	**Level of agreement: if things continue on their present course, we will soon experience a major ecological catastrophe.**	**0.47**	0.11	-0.02
I15	Level of agreement: plants and animals have as much right as humans to exist.	0.24	0.03	0.36
I16	Level of agreement: humans were meant to rule over the rest of nature.	0.40	-0.25	0.32

[3] The α'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: ≥0.90 excellent reliability; 0.70 ÷ 0.90 high reliability; 0.50 ÷ 0.70 moderate reliability; ≤0.50 low reliability.

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

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

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

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

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

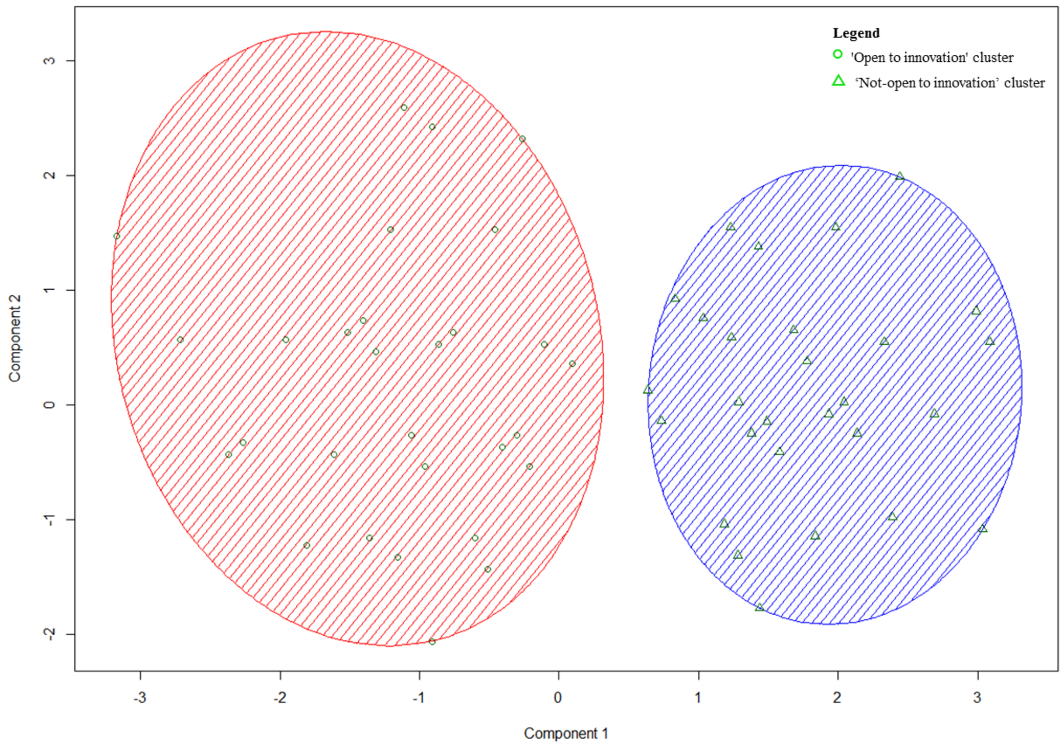


Table 5: Final cluster centres

	Cluster	
	1 (Not open to innovation)	**2** (Open to innovation)
I12	3	4
I14	3	4
I17	3	4
I21	3	4

Table 6: ANOVA

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

Table 7: Number of cases in each cluster

Cluster	***1***	35
	2	55
Valid		90
Missing		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.

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

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

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

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

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

We now examine in detail the results in light of the different specifications used for the inclusion of the IPA variable. In Specification 1, the IPA coefficient is positive, indicating that the peers' attitude of being open to innovation tends to increase the utility of purchasing an EV, but this is not very significant, at 85% confidence level, which does not confirm H1. The dummy formulation of the social influence variable has also been tested and found to be even less significant. The significance of the effect of the IPA variable is instead very large in Specification 2, i.e. IPA has a significant positive effect on the *'openness to innovation'* attitude of the survey respondent, at more than 95% confidence level, which confirms H2. Therefore, the 'open to innovation' attitude of the individual is strongly related with the 'open to innovation' attitude of his/her peers; this indirectly influences the perception of EV utility through the effect of the latent variable included in the choice model component. Finally, looking at the results of Specification 3, the latent variable does not seem to be manifested by the IPA variable used as an indicator (see "Coefficient indicator IPA"), as it is only significant at 27% confidence level, which does not confirm H3. The combined inclusion of IPA in both the choice model component and the structural model component does not produce any significant results.

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

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

Table 8: Model results

	Specification 0			*Specification 1*			*Specification 2*			*Specification 3*		
Variable Names	***Value***	***Robust t-test***		***Value***	***Robust t-test***		***Value***	***Robust t-test***		***Value***	***Robust t-test***	
Choice Model Component												
ASC (EV)$^{\Psi}$	-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	***
Structural Model Component												
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 – *1st 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 γ	-1.40	-5.66	***	-2.53	-5.12	***	-2.62	-4.05	***	-1.42	-5.27	***
Measurement Model Component												
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	***
N.param.	27			28			28			30		
N.obs.	684			684			684			684		
N.draws	2000			2000			2000			2000		
Final LL over choices	-469.07			-466.59			-466.41			-523.46		

*** p-value smaller or equal 5%; ** p-value between 5% and 10%; * p-value between 10% and 20%

$^{\Psi}$ (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**
Specification 1	*Specification 0*	4.94	0.03
Specification 2	*Specification 0*	5.30	0.02

Model	**AIC_c Value**
Specification 0	994
Specification 1	992
Specification 2	991
Specification 3	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 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%).

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

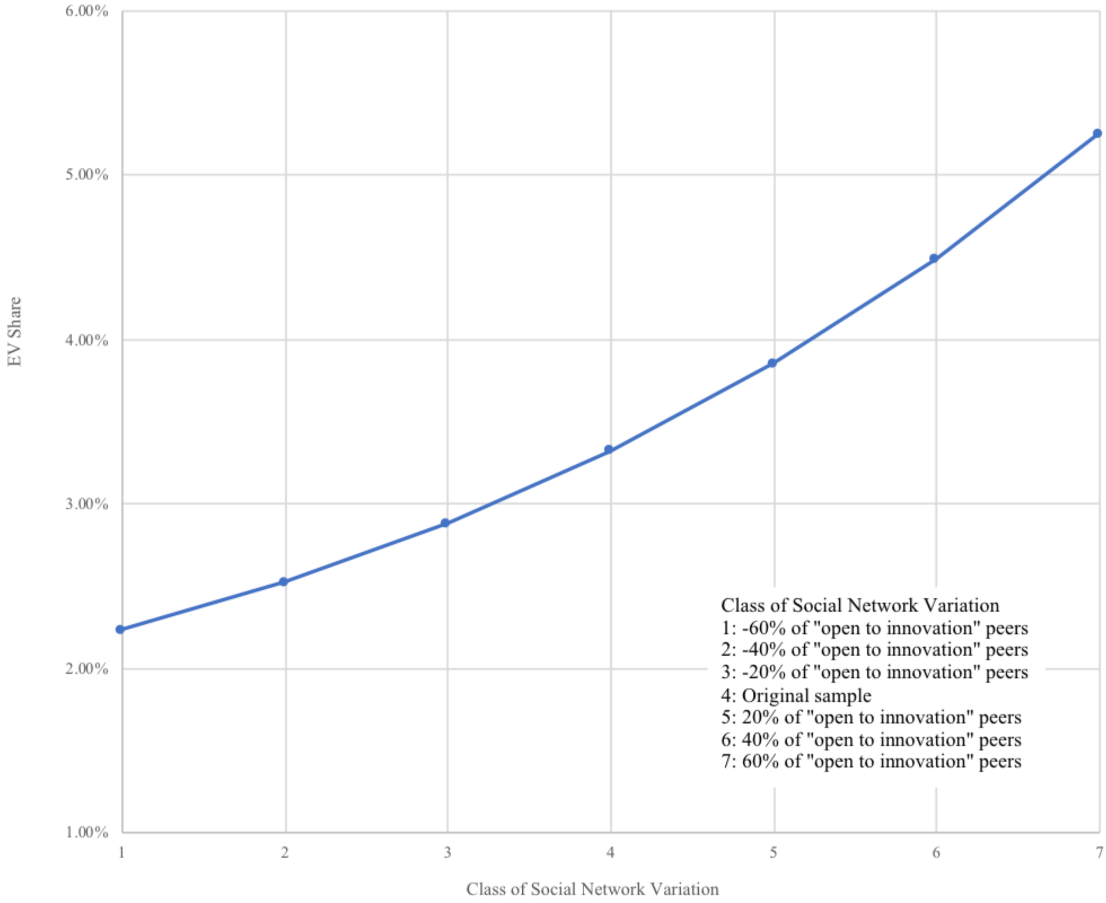


Figure 7: Sensitivity analysis of IPA variable scores - Weight Variation

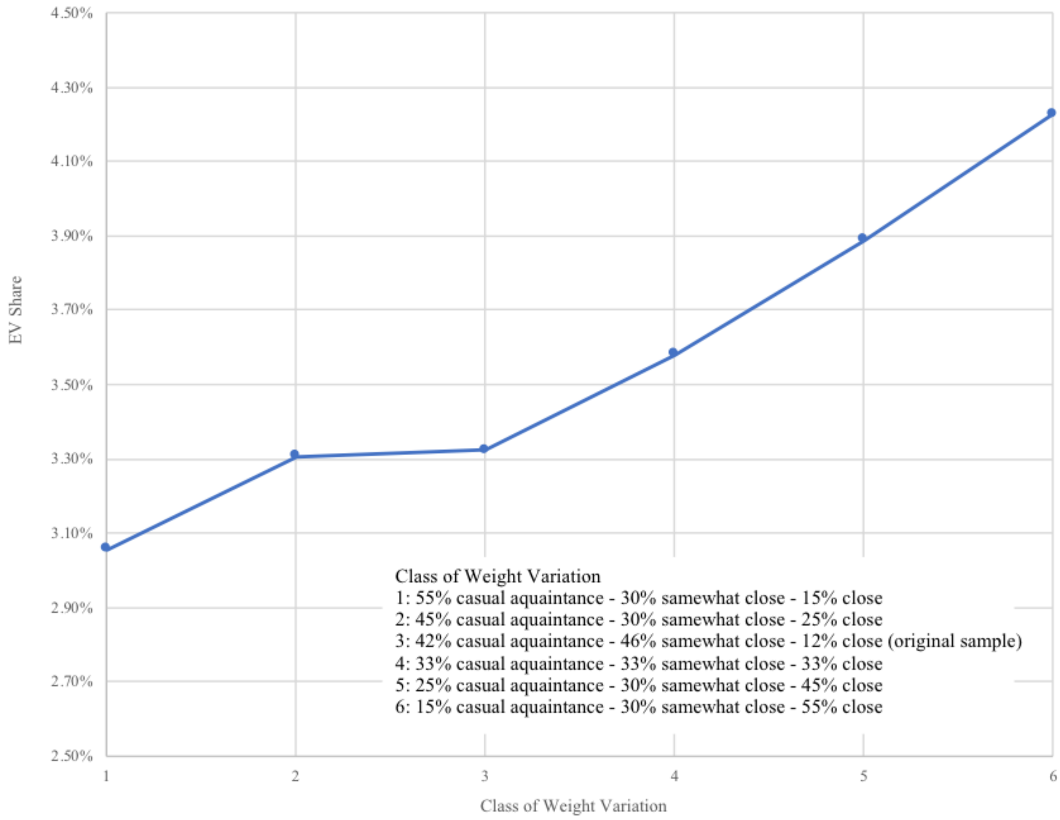
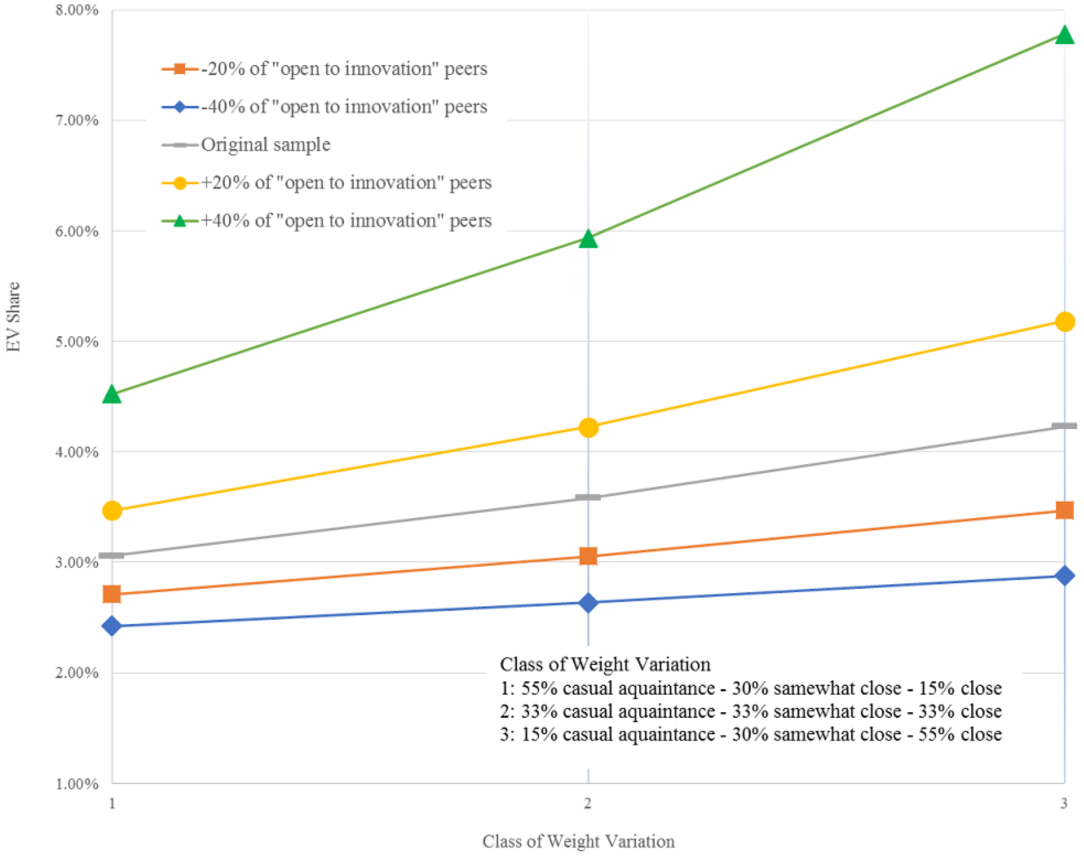


Figure 8: Sensitivity analysis of IPA variable scores - Combined Social Network and Weight Variation



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

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

An interesting and genuinely novel application of the proposed methodology would, therefore, be to combine 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 a few observable innovators and, subsequently, a 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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