Modelling live social interactions and indirect social influence affecting the adoption of transport technologies and services: a bike sharing case study

Francesco Manca, Aruna Sivakumar

Urban Systems Laboratory, Centre for Transport Studies, Department of Civil and Environmental Engineering, Imperial College London, UK

Keywords: Social influence, Live social interactions, Inertia effect, Hybrid Choice Model.

1. *Motivation and objectives*

Social influence is an important factor in the decision-making process of an individual [1, 2]. Especially in contexts of adoption of new technologies and services, it appears reductive to investigate individual's behaviours and responses without considering the inherent social network influence, which can help for a better understanding of the dynamics behind their choices. The processes generated by social influence have been extensively analysed in other disciplines, such as sociology, social psychology and economics. Revising and resuming these studies, Axsen and Kurani [3] conceptualised the dynamics of social interaction processes on intentions and adoptions of new technologies. Another important social influence process discussed in their previous review paper, Axsen and Kurani [4] is the conformity process. Individuals perceive how other people behave and tend to conform under the pressure of subjective and social norms [5]. In fact, norms can influence cognitive processes which generate the intention to a certain behaviour and can also affect the decision making process of the individuals. Besides social interaction and conformity processes, Ng [6] defined an additional level of indirect social influence which is characterised by elusive information and absence of resistance and reinforcement. This influence is very difficult to explain as the individual are not even aware of it (i.e. when a person develops similar attitudes to most of his/her peers).

In transport research, previous methodologies have mainly focused on the inclusion of conformity in quantitative models, i.e. discrete choice models, and have emphasised the analyses of user behaviours at social level, i.e.

friends, family and colleagues, with respect to simplified analyses at the individual level. Although there have been significant research advancements, it is yet not clear how to quantify and incorporate in a suitable modelling methodology different social influence effects. For instance, the previous studies lack a modelling methodology that can simultaneously capture real social interaction processes and indirect social influence effect (i.e. the influence described by Ng [6]).

Starting from two previous works, Manca et al. [7] and Manca et al. [8] which respectively discussed how to quantify the real/live social interactions and the indirect influence generated by peers' attitudes in a social network, this paper shows an analytical framework to account simultaneously for both processes which can impact the individual's awareness, assessment and self-concept (i.e. the layers of the 'Reflexive Layer of Influence' construct [3]). The proposed analytical framework helps analyse whether the social influence affects the utility of the alternatives, also playing a role in confounding the modified perception of the observable variables and the available alternatives.

1.1. Direct social influence measures

The direct social influence measures are a consequence of social interactions. These measures are conceptually based on the framework developed by Axsen and Kurani [3]. The RLI framework describes three perspectives through the processes (or layers) of social influence which are a direct effect of social interactions within a social network:

- Diffusion: a process of basic understanding of technology in which awareness of this technology (or service) is diffused during social interaction.

- Translation: a process of technology/service evaluation in which the information is translated into an evaluation of benefits and drawbacks, which can also be translated by each actor differently.

- Reflexivity: a process of self-concept influence in which discussion about the new technology/service can help one or more of the individuals to reflect upon their own values, lifestyle or self-concept.

Besides the direct social interaction processes, the conformity process is included into the general analytical framework because conformity is not completely divisible from social interactions. This helps to give a clearer and more comprehensive overview of the overall social influence processes.

1.2. Indirect social influence measures

The indirect social influence measures are defined by the interactions between two different types of information: psychometric measures that characterise latent motivational characteristics of the individual, and the tie strengths [8]. The psychometric measures refer to the Theory of Planned Behaviour (TPB) by Ajzen [9] for the definition of latent characteristics. This theory assumes that the intentions behind a behaviour capture motivational factors. These intentions indicate the degree of people's willingness to try and the degree of effort that is planned to be practised in order to perform the behaviour [9]. A behavioural intention is formed with the combination of three elements: attitudes, subjective norms towards the behaviour and the perceived difficulty to perform the behaviour.

2. Data

The case study analysed in this paper refers to the intention within a cohort of students to use a pro-environmental transport modal service (i.e. bike sharing) during a public transport strike [7]. Two different types of survey were performed in 2018 within the student cohort to gather the needed information: a stated preference survey and an attitudinal survey. The targeted SP experiment was designed to explore how alternative attributes affect the individuals' choice in the hypothetical scenario. Information on normative conformity (i.e. the hypothetical adoption rate within the social network) and real social interactions were also collected. In particular, for the former, a group discussion among the respondents was undertaken between two subsequent stated preference experiments, SP1 and SP2. The group discussion enabled us to investigate cognitive and interpersonal mechanisms that can generate awareness on the pros and cons of cycling and bike sharing. Moreover, considering the "Reflexive Layers of Influence" (RLI) framework, the processes generated by social interactions (diffusion, translation and reflexivity) are measured and quantified.

In the attitudinal survey, the students gave information on Theory of Planned Behaviour constructs (attitudes, subjective norms and perceived behavioural controls concerning cycling). Moreover, respondents were specifically asked to name someone in the class they interacted with. They shared information about their social relationships with each person that was named. Specifically, they stated their social proximity to the contact ('not close', 'casual acquaintance', 'close', 'very close'), frequency of conversion with the classmate about commuting between home and university and other occasions of travelling within London.

3. Modelling Methodology

The proposed modelling framework is complex and built upon the classical discrete choice model formulation, which allows us to investigate the choice behaviour of individuals and how this behaviour can change during the decision-making process. Different techniques are then used to incorporate social influence and latent attitudinal constructs in the discrete choice model framework.

The measures of real/live social interactions and social influence processes (diffusion, translation and reflexivity) are included in a specific choice modelling formulation to evaluate their effect on the individuals' choice. Specifically, the real social interaction is evaluated by incorporating the inertia and the propensity to change generated during the group discussion [7].

About the quantification of indirect social influence, as in Manca et al. [8], first, an exploratory factor analysis is used to identify these latent constructs from the psychometric indicators available from the survey data[1]. Having identified the subset of indicators specific to each latent construct, a cluster analysis is used on such indicators to group respondents with similar indicator levels for specific factors. Subsequently, the social influence variable is specified by interacting clusters with social relationship measures (i.e. the social proximity). In order to understand whether individuals with a specific attitude can influence peers in their social network, the individual's peer attitude (IPA) can be included in different components of a Hybrid Choice Model.

3.1. The joint hybrid choice model accounting for direct and indirect social influence

A Hybrid Choice Model formulation that enables us to account for all the individual attitudes and the individual's social network effects has been used. This model is estimated using a joint SP1/SP2 dataset, incorporating the latent variables and including direct and indirect measures of social influence and social interactions. Its Choice Model Component, whose utility

[1] In this specific case study, the identified latent constructs are "Propensity towards cars", "Propensity towards cycling", "Cycling ease" and "Environmental concern". The model shown in this paper only includes the "Latent propensity towards cars" variable which is the only latent variable returning significant results with the model estimations. The statements characterising this construct are: "*I would not like to cycle when it rains*", "*In the city where you previously lived having a car is a must*" and "*In the city where you previously lived most people drive*".

function is associated with alternative a in the stated preference task choice $t = [1, ..., T]$ by the individual i, can be specified as:

$$U_{ait}^{SP1} = V_{ait}^{SP1} + \beta_{aAtt}^{SP1} Att_i + \beta_{SN}^{SP1} SN_{ait}^{SP1} + \xi_{ai}^{SP1} + \varepsilon_{ait}^{SP1}$$
$$U_{ait}^{SP2} = \phi(V_{ait}^{SP2} + \beta_{aAtt}^{SP2} Att_i + \beta_{SN}^{SP2} SN_{ait}^{SP2} + \beta_{RLI}^{SP2} RLI_{ait}^{SP2} - I_{ait}^{SP2} + \xi_{ai}^{SP2} + \varepsilon_{ait}^{SP2}) \tag{1}$$

where $V_{ait} = ASC_a + \beta_{aX} X_{ait} + \beta_{aS} S_i$ is the systematic utility, including alternative characteristics X_{ait} and socioeconomic variables S_i; SN_{ait} is the effect of the social norm variable capturing the social conformity through information on the adoption rate within the social network; RLI_{ait} is the vector of RLI variables and I_{ait}, the inertia effect, defined in accordance to the general formulation by [10]:

$$I_{ait}^{SP2} = \theta_{ait}^{SP2} \ (\dot{V}_{kit}^{SP1} - \dot{V}_{ait}^{SP1}) \tag{2}$$

which implies that, during SP2 choice tasks, the individual i also compares the systematic utility regarding the characteristics of the alternative a in SP1, $\dot{V}_{ait}^{SP1}$, to the systematic utility regarding the characteristics of the alternative k actually chosen in SP1 choice tasks, $\dot{V}_{kit}^{SP1}$. In this case, θ_{ait}^{SP2} can vary systematically, randomly and as a function of the group's perception variables of the transport technology specified as $\theta_i = \theta + \delta_i \sigma_\theta - (\theta_{SI}^{St} \ St_{iG}^{+} + \theta_{SI}^{W} \ W_{iG}^{-})$.

The Structural Model Component associates the latent variable to socioeconomic characteristics S' of the individual i. Moreover, the IPA variable is included to take into account the indirect social influence generated by the peers' attitudes (i.e. the peers' propensity towards cars):

$$Att_i = c + \delta S'_i + \psi IPA_i + \gamma_i \tag{3}$$

where δ and ψ are the parameters associated with the socioeconomic characteristics and the IPA respectively, c is the intercept and γ_i is the error term, assumed to be normally distributed $N(0, \sigma_\gamma)$.

Finally, the specification of the measurement model component, which links the latent variable to the indicators I_{fi} through f equations and for each individual i, is:

$$I_{fi} = d_f + \theta_f Att_i + \nu_{fi}, \quad with \;\; f = 1, ..., F \tag{4}$$

where θ_f is the coefficient characterising the latent variable, d_f is the intersect and ν_{fi} is the error term, assumed to be normally distributed $N(0, \sigma_\nu)$.

4. Results

The results of the hybrid choice model including all the different social influence processes are shown in Table 1.

4.1. Choice Model Component

The choice model component includes all the variables of LoS, the inertia effect, the normative conformity and the latent variable. The parameters regarding the Level-of-Service of the alternatives shared taxi (*Taxi*), bike sharing with docking station (*BSd*) and dockless bike sharing (*BSw*) and the weather conditions are all statistically significant with a confidence level above 95%. Regarding the social norm variable included in the model as generic in *both BS*, the higher the hypothetical adoption rate of peers was, the greater the positive effect of the variable on bike sharing preference.

The inertia variable is very significant and positive for *BSw*, indicating the presence of inertia from SP1 to SP2. Hence, if people had previously chosen a mode other than *BSw*, they would again prefer that mode over *BSw*. The coefficients of the interaction between inertia and perceptions are similar in magnitude and significance but opposite sign suggesting that the benefit of 'avoiding congestion' reduces the inertia effect and consequently increases the probability of choosing *BSw* while the drawback of 'safety concern' increases the inertia effect and, therefore, reduces the propensity to change to another mode during the SP2 experiment. No significant results were found for the inertia variable included in *Taxi* and *BSd*.

The different measures of RLI are included as generic in *both BS* of the SP2 part but only the translation variable among all the RLI tested is significant. The negative sign of this variable's parameter suggests that the respondents do not consider changing mode as high beneficial for themselves.

The latent variable ('*Latent propensity towards cars*') is included as generic in the utility of *both BS*, its coefficient is always highly significant at more than 95% confidence and with a negative sign; therefore, it is inferred that an individual characterised by 'propensity towards cars' is strongly associated with the decrease of utility of *both BS* with respect to the conventional *Taxi*, thus, indirectly boosting the demand for *Taxi*.

4.2. Structural Model Component

The structural model component indicates the socioeconomic characteristics of the individual with a 'propensity towards cars'. This individual are very likely to be: male (since the dummy variable associated to this characteristic has a positive and very significant coefficient), younger than 25 years as suggested by the highly significant negative coefficient on the dummy variable for Age ≥ 25, not with high cycling experience (this variable coefficient is in fact negative and significant). In addition, this individual is likely to be part of a social network in which the peers are also inclined towards cars. The 'propensity towards cars' attitude of the individual is therefore strongly related with the 'propensity towards cars' attitude of his/her peers; this indirectly influences the perception of Bike Sharing utility through the effect of the latent variable included in the choice model component.

4.3. Measurement Model Component

Finally, the results of the measurement model component show significant coefficients of the latent variable (for indicators 2 and 3, always greater than 95%). This confirms that the results of the exploratory factor analysis and the presence of correlation between the indicators that identify the latent variable construct.

Table 1: Complete HCM with direct and indirect influence variables

			HCM	
		Parameters	**Value**	**Robust t-test**
Choice model	**LoS**	***ASC (both BS)***	11.10	6.88**
		ASC (Taxi)	9.68	4.58**
		Travel Cost (both BS)	-0.75	-6.41**
		Travel Cost (Taxi)	-0.52	-3.17**
		Travel time (both BS)	-0.12	-2.97**
		Travel time (Taxi)	-0.14	-2.65**
		Walking time_gen (both BS)	-0.17	-7.23**
		Weather light rain (Taxi)	3.09	5.81**
		mu (both BS)	5.00	6.57**
		mu (Taxi)	2.32	6.60**
		phi (Scale factor)	1.08	10.39**
	Normative conformity	***Social norms (both BS)***	0.38	3.85**
	Inertia & interaction with perceptions	***I (BSw_SP2)***	0.53	2.15*
		I * Avoid congestion (BSw_SP2)	-0.71	-3.03**
		I * Safety concern (BSw_SP2)	1.05	3.46**
	RLI	***Operation - diffusion (both BS_SP2)***	0.11	0.37
		Own benefit - translation (both BS_SP2)	-2.54	-7.98**
	Latent construct	***Latent - Propensity to cars (both BS)***	-0.14	-3.50**
Structural model		***Age (>25yo)***	-0.16	-2.30*
		High cycling experience	-0.08	-2.29*
		Gender - Male	0.14	2.30*
		IPA (Propensity to cars)	0.50	2.28*
		LV Constant	4.65	40.24**
		LV γ	-1.55	-3.55**
Measurement model		***Intercept indicator I2***	-9.81	-1.55
		Intercept indicator I3	-17.80	-1.86
		Coefficient indicator I2	2.95	2.26*
		Coefficient indicator I3	4.54	2.29*
		Standard deviation indicator I1	-0.45	-1.88
		Standard deviation indicator I2	-0.24	-2.08*
		Standard deviation indicator I3	-3.96	-17.10**
Results		***N.param.***	31	
		N.obs.	816	
		N.draws	2000	
		Final LL	-725.15	
		Rho2	0.393	

$^{**}\, p-value \leq 0.01$ $\quad ^{*}\, p-value \leq 0.05$

5. Conclusions

The tested modelling structure enables us to disentangle and quantify both direct and indirect social influence effects in the decision-making process of the individual and, consequently guarantees a better explanation of the heterogeneity. The combined model adds a further degree of completeness in explaining the travel choice behaviours of the interviewed respondents. Indeed, it makes it possible to relate at the same time:

- social influence processes of diffusion, translation and reflexivity
- social live interactions effects such as awareness of benefits and drawback of a new technology/service
- conformity processes related to social norms such as the hypothetical adoption rate in the cohort
- indirect influence processes related to psychometric factors such as attitudes, norms and perceived behavioural control.

References

[1] C. F. Manski, Identification of endogenous social effects: The reflection problem, The Review of Economic Studies 60 (1993) 531–542.

[2] W. A. Brock, S. N. Durlauf, Discrete choice with social interactions, Review of Economic Studies 68 (2001) 235–260.

[3] J. Axsen, K. S. Kurani, Social influence and proenvironmental behavior: The reflexive layers of influence framework, Environment and Planning B: Planning and Design 41 (2014) 847–862.

[4] J. Axsen, K. S. Kurani, Social influence, consumer behavior, and low-carbon energy transitions, Annual Review of Environment and Resources 37 (2012) 311–340.

[5] R. B. Cialdini, N. J. Goldstein, Social influence: Compliance and conformity, Annu. Rev. Psychol. 55 (2004) 591–621.

[6] S. H. Ng, Influencing through the power of language, Psychology Press, 2001, pp. 185–197.

[7] F. Manca, A. Sivakumar, J. W. Polak, The effect of social influence and social interactions on the adoption of a new technology: The use of bike sharing in a student population, Transportation Research Part C: Emerging Technologies 105 (2019) 611–625.

[8] F. Manca, A. Sivakumar, N. Daina, J. Axsen, J. W. Polak, Modelling indirect social influence on choice behaviour: An electric vehicle purchase choice case study, Available at SSRN 3502972 (2019).

[9] I. Ajzen, The theory of planned behavior, Organizational Behavior and Human Decision Processes 50 (1991) 179–211.

[10] V. Cantillo, J. d. D. Ortúzar, H. C. W. L. Williams, Modeling discrete choices in the presence of inertia and serial correlation, Transportation Science 41 (2007) 195–205.