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X Complexity and Travel Behaviour

Modelling influence of social interactions on travellers' behaviour using a multi-agent simulation

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The planning and design of transport systems have an important part in leading travellers to more sustainable and efficient choices. Car-dependence is a prominent problem to be solved in order to reduce traffic congestion. It also affects the general efficiency with which people can travel in urban areas, the environmental impacts of traffic, the structure of towns and settlements and consequently the liveability of the cities. Traditional models of travel behaviour, commonly looking at aggregated choices tend to ignore the complexity of the travel choice problem, where many decision makers influencing each other in a dynamic process of social interactions in various domains and through various types of social network. In this work we present a methodology to model social interactions and their influence on travel choices. The methodology, based on multi-agent simulation, is explained using an example demonstrating the influence of the social interactions on travellers' behaviour during the implementation of a demand management measure. Some behavioural insights obtained from the example are also discussed.

X.1 Background

The problem of car-dependence is a key issue to be solved in order to reduce traffic congestion, which is responsible for a considerable part of environmental pressures. By reducing traffic congestion people can travel more efficiently (e.g. less travel time/cost, less environmental pollution) and with equal importance, to keep the existence of public transport services. Many practical transportation policy issues are concerned with people's choice of transportation mode. It affects the general efficiency with which people can travel in urban areas, the environmental impacts of traffic, the structure of towns and settlements and

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The private car is the dominant means of transportation in most areas and it contributes considerably to traffic congestion. Public transport has a key role in travel mode choice-related policies since it makes use of road space more efficiently than private cars. If some car users could be persuaded to use public transport instead of cars then the rest of the car users would benefit from improved levels of service as the traffic is less congested (unless further car traffic is generated). However, car use provides the individual driver with a number of immediate advantages which make the users unwilling to switch to public transport. A car appears to be a cheap form of transportation (Van Vugt et al., 1998), effective and efficient for multi-purpose trips (Mackett, 2003), and has a link to feelings of independence and convenience (Tertoolen et al., 1998).

A demand management measure (or often called Transportation Demand Management or TDM) is the application of a plan or policy aimed at changing or reducing demand for car use by encouraging the behavioural change of people's choices of travel. Demand management measures are utilized to address the problem of car dependence by incorporating structural interventions ('hard' measures) as well as psychological interventions ('soft' measures). Hard measures include policy interventions that alter the objective features of the decision situation by changing the incentive patterns associated with cooperation and non-cooperation. Examples of hard measures may include changing payoff structure (e.g. congestion charging), reward-punishment (e.g. incentives for public transport users, restriction on car parking), and situational change (e.g. residential or workplace relocation). Soft measures can be defined as policy interventions that are aimed at influencing attitudes and beliefs that may guide people's cooperative and non-cooperative behaviours. Soft measures are more persuasive than hard ones. They include increasing individuals' awareness of the environmental impacts of excessive car use (e.g. travel awareness campaign), providing advice and information to encourage the use of alternative modes of travel (e.g. travel plan, individualized marketing) and promoting alternative ways of using car (e.g. car-sharing).

Hard measures, which concentrate on changing personal material incentives associated with travel mode options (e.g. time, cost, and comfort), seem to be more effective than psychological interventions, since enforcements by the authority are also at force. Soft measures are voluntary by nature and have no economic consequences (e.g. penalty from the authority) if travellers do not participate in the measures, so that the measures may become attractive for travellers as they are not obliged to participate in. Some success stories have been reported in recent pilot projects on soft measures (Jones and Sloman, 2003; Cairns et al., 2004; Stopher, 2005). However, soft measures have also drawbacks as it is difficult to ensure the sustainability of travellers' participation in a long run.

It may be argued that the effectivenesses of a soft measure could be enhanced if more consideration and emphasis is given to the support of social aspects of human behaviour. Given the fact that behavioural change does not take place in a social vacuum, broader society and its social values have important roles to play. Social-psychological aspects of travel behaviour, including *social interaction*, *social learning/imitation*, and *social influence*, may influence travellers' behaviour. Better understanding of these aspects will provide us with some informed behavioural insights about the potential for utilizing them to encourage travellers' change of behaviour. An agent-based simulation is used in this study to model the roles that social aspects may have in influencing travellers' behaviour during the implementation of a policy measure.

The diffusion process of compliance with a demand management measure has become our interest as it may have an important role in encouraging behavioursal change. Jones and Sloman (2003) argued that the existence of the 'snowball effect', a phenomenon where long-term effects may be greater than short-term ones, would increase the effectiveness of soft measures over time. They stated that, there is some evidence that the change may be very slow at first, but then accelerate as people see their colleagues and neighbours changing their travel behaviour. In the implementation of voluntary household travel behaviour change programs, Ampt (2003) argued that strategies that require households to diffuse information both between households and ultimately across communities are likely to be effective. Stopher (2005) added the importance of diffusion effects in the implementation of voluntary programs by stating the need to measure the effects in schools, workplaces, and other locations. Spreading information by 'word-of-mouth' is the most effective way for diffusion and reinforcement (Stern et al., 1987). When a person tells someone about what he is doing, he is both reinforcing his own behaviour in the process and giving a level of commitment. This way of communicating is often called 'word-of-mouth' communication. A study by Shaheen (2004) also considered this word-of-mouth communication as a means to diffuse the change of behaviour in a car-sharing program.

To gather understanding on the social aspects, it is important to explore their influence on travellers' behaviour using empirical and experimental studies based on observations of their choices during field and laboratory studies (see examples in Sunitiyoso et al., 2007, 2008). However, a simulation-based study is also a valuable line of research. Jager et al. (2002) argued that a simulation research does not replace empirical research, but it has two main functions. First, it may function as a complementary research tool which enables researchers to explore complex (multi-factorial) research fields and to identify promising conditions for further (empirical) research. Second, a simulation model may be used to answer questions emerging from empirical research (laboratory or field), demonstrating that complex phenomena are sometimes resulted from simple dynamics.

X.2 The complexity of social interactions in travel behaviour

Travel behaviour is a result of a complex and dynamic process involving a sequence of adaptations overtime. The timing and frequency of many events may lead to different patterns of travel behaviour. As a complex system, the main element of travel behaviour is travellers themselves as the actors of travel decision making. Personal factors such as attitudes, preferences, and habits influence the behaviour of a traveller. Interactions between travellers in various interaction domains (neighbourhood, school, workplace, etc) using various types of social network (lattice structured, random network, etc) may also have important roles to play. Travellers are also heterogeneous; some travellers interact with other travellers and take other travellers' behaviour into consideration before making a travel choice decision. Other travellers may stick to the same travel choice by habit. They are not easily influenced to change their choice to another choice. The aggregate interactions of the interacting travellers would later contribute to the dynamic of aggregate behaviour of travellers in the transportation system. Other elements such as policy interventions by the transportation authority are external elements that may also influence travellers' behaviour. The large number of variables involved and the variety of their interactions contribute to the complexity of travel behaviour.

Social interaction

Social interaction is necessary for a successful social learning and influence from an individual to other individuals. The interaction exists whenever an individual is involved in an interdependence situation with other individuals. Interdependence can be explained by a collective action (e.g. social dilemma) where there exists impossibility of exclusion, which means that no member of the group engaged in collective action can be excluded from enjoying the benefits of the group's efforts (Huberman and Glance, 1993). Messick (1985) defines interdependence in relation to preferences by stating the fact that individuals are not indifferent to the outcomes received by others. Interdependence of choice may create a situation where travellers sometimes take into account and are concerned about choices by other travellers (Van Lange et al., 2000).

In this study, we consider that social interactions occur beyond residential neighbourhoods. There may be multi-dimensional relationships between individuals, which are built based on similarities of 'social club' domains, including workplace, non-work activity club and also within a household. However, we do not focus on intra-household interactions. The possibility of repeated interactions between individuals differs from one social club to another. For example, a workplace gives more opportunity for interaction than a sport/leisure club since colleagues of the same workplace work around five days a week at the same place, whereas members of sport/leisure club may only meet once or twice a week.

Social network may affect the spread of influence (Kempe et al., 2003). The structure of a network has an important role to determine a successful diffusion process of information. There are many kinds of communication structures that may exist between individuals. Nakamaru and Levin (2004) investigated four structures: complete mixing (each individual interacts with the others at random), lattice (each individual interacts with his neighbours with some probability), power-law-network (a few influential people have more social contacts than the others) and random graph network (the number of contacts follows a Poisson distribution). The types of social network may differ between different 'social club' domains. For example, lattice-structured network is more likely to exist in a neighbourhood domains while complete mixing in a non-work activity club domain.

Social learning

Change of behaviour is a dynamic process that occurs over time and may involve a learning process. The concept of *individual learning* suggests that individuals learn from their past experience and utilise an adaptive decision making process to cope with uncertainty. There is also another form of learning, *social learning*, where individuals learn from others' experiences or observed behaviours. In travel behaviour modelling, the individual learning concept has often been studied (for review, see Arentze and Timmermans, 2005), while social learning has not been investigated intensively. It is quite surprising since some evidence from other disciplines (e.g. economics and behavioural sciences) have shown that this kind of learning process is influential and important (e.g. Pingle, 1995; Offerman and Sonnemans, 1998).

In social learning, decision makers observe the behaviours or preferences of others prior to making a choice, therefore they can reduce their efforts in comparing and analysing all possible choices by themselves. Individuals can use several mechanisms in order to learn from others as suggested by Henrich (2004); these include conformist transmission (imitating high frequency behaviours), payoff-biased transmission (imitating other individuals who are more successful), self-similarity transmission (imitating other individuals with similarity in some traits) or normative transmission (following the common behaviour in the group according to social norm).

Social influence

There is a slight difference between social learning and social influence. In social learning, the change of judgments, opinions and attitudes of an individual is a result of active search for information by the individual, where as in social influence, the change is a result of being exposed to other individuals (Van Avermaet, 1996).

There are two types of social influence: majority influence (conformity) and minority influence (innovation). Majority influence can be shortly defined as the majority's efforts to produce conformity on the part of a minority, whereas minority influence can be defined as the minority's effort to convert the majority to its own way of thinking (Sampson, 1991). Majority influence has a strong relation with a form of social learning transmission, the conformist transmission, which is a psychological propensity to preferentially imitate high frequency behaviourss or the most common (majority) behaviours.

In this research, minority influence becomes the point of interest as other studies indicated the importance of considering the influence of 'key people' in diffusion of participation in a demand management measure (e.g. Ampt, 2003). 'Key people' are not necessarily traditional leaders, but they can be 'trusted persons' with a respected reputation in community. The influence of these 'key people' is called minority influence. In the model, minority influence is investigated by introducing a situation where a few influential agents (independently or in group) have more power to influence others whom they communicate with. The strength of their influence is derived from the reputation built from their consistency of choice to comply with the measure (Van Avermaet, 1996; Sampson, 1991). Involving key people (not necessarily traditional leaders, but 'trusted others' in the community) will provide more advantages since people are more willing to hear from someone who is trusted, respected or perceived to have similar values. This is related with the idea of minority influence where a few influential agents are able to influence the opposing majority to the minority's way of thinking. Individuals are more willing to hear from someone who is trusted and respected as a consistent person. For example: a suggestion to car share by a consistent car sharer, who has been car sharing regularly in a considerable period of time, would have more influence than that of other individuals' who have not done so.

The potential effects of these three social aspects on travellers' decision making and behaviour are investigated using a multi-agent simulation model as discussed in the following section.

X.3 Agent-based approach for simulating travellers' behaviour

An agent-based model can be defined as a computational model, which represents individual agents and their collective behaviour (Parunak et al., 1998 and Shalizi, 2003). An agent-based model represents individuals, their behaviours, and their interactions, rather than the aggregate of individuals and their dynamics. The application of this approach in transportation modelling is still in infancy, although it offers many benefits in the study of behaviour (in transportation context: e.g. Nakayama et al., 2001; Arentze and Timmermans, 2006; Avineri, 2006; in non-transportation context: Henrich and Boyd, 1998; Kameda and Nakanishi, 2002).

In travel behaviour modelling, the idea of utilizing a multi-agent model to better understand the dynamic of travellers' change of behaviour has not been given much consideration until recently, despite its potential to provide a different 'flavour' on travel behaviour studies by deriving informed insights from the results of simulation experiments (e.g. Kitamura et al., 1999; Sunitiyoso and Matsumoto, 2007; Sunitiyoso et al., 2006). In a multi-agent model, decision making rules and parameters used by individuals can be based on decision making processes revealed from empirical studies (e.g. behavioural survey, laboratory experiment) as well as behavioural theories. A multi-agent simulation model is able to elucidate the dynamics of decision making processes, showing what course of 'evolution' a certain behaviour could have looked like over time. Travellers' behaviour can be represented by the behaviour of autonomous agents in a simulation model. The model is also used to represent social interactions between agents which occur through various interaction domains (e.g. neighbourhood, workplace/school, etc).

In studying the effects of a treatment/intervention on individuals, a simulation experiment is able to handle the interactions of a large number of individuals with each other in a large and complex transportation system. It also makes possible for conducting a large number of repetitions (time periods), which enable the researcher to observe whether individuals' choices converge to an equilibrium point or not, how they converge and the dynamics before convergence. It may also provide predictive value in forecasting travellers' behaviour in different kind of situations, and to know how robust the results are in different parametric conditions.

The multi-agent simulation approach presented in this study focuses on (intangible) interactions between individuals, while physical interactions between the individuals and transport or urban environment are beyond the scope of the study. Other studies have indicated that agent-based models are also able to represent the interactions of physical entities such as pedestrians on streets or cars on roads (e.g. Batty, 2005, pp 263-318).

In the next section, we present an example of the way a multi-agent simulation model can be used to simulate and understand the influence of these social-psychological aspects on traveller's behaviour and the performance of the overall system.

X.4 Simulating the influence of social interactions on travellers' behaviour

The research methodology consists of two stages, a behavioural survey and a simulation experiment. In the first stage, a *behavioural survey* is conducted to obtain information regarding mechanisms of social interaction and social learning in addition to those derived from literatures, as well as parameters required for the simulation model. There survey respondents (N=178) are students in the Faculty of the Built Environment, University of the West of England - Bristol. Car-sharing, as a 'soft' demand management measure, was used as a case study in the survey (and is used in the second stage of study, the simulation experiment). The survey enables an estimation of some of the simulation model's parameters (e.g. weights of other agents' influence, the proportion of influential minority, reputation of agents) and initial values for the variables (e.g. agents' preferences, choices, level of compliance), while other parameters and variables are estimated based on theoretical assumptions as they are difficult to be measured empirically. In the second stage of the study, the *simulation experiment* utilizes an agent-based simulation model to simulate and analyse behaviours of individuals. We focus our discussions in this chapter on the second stage of study, the simulation experiment.

The model consists of four main sections: social interaction, social learning and influence, decision making, and individual learning (from the outcome of previous decision). The algorithm of the model is then developed as simply illustrated in Figure X.1. The algorithm starts with initialization process of assigning a number of agents into so-called 'social' club domains (*neighbourhood*, *course of study*, and *non-study social club*). It is assumed that within each club each member can meet (not necessarily followed by communication) any other members in a lattice structured network for the *neighbourhood* domain and in random manner (complete mixing) for other type of 'social' clubs. The frequency of meeting depends on the type of interaction domain. For example, an agent (individual student) meets other agents (fellow student) more often in a course of study than in a non-study social club (see Table X.1).

In the simulation model, social interaction is represented by two processes: *meeting* and *communicating*. These processes may occur in any social club domain depending on the day of the week whenever agents (who represent individuals) involve with activities in the domain. Meeting is defined as a process where two agents meet each other without engaging in an intensive communication involving an exchange of information. Communication may follow the meeting if there is a 'mutual agreement' between them, which depends on whether they are both closely connected or not (represented by the value of perceived degree of relationship) and on whether a threshold for communicating has been exceeded or not.

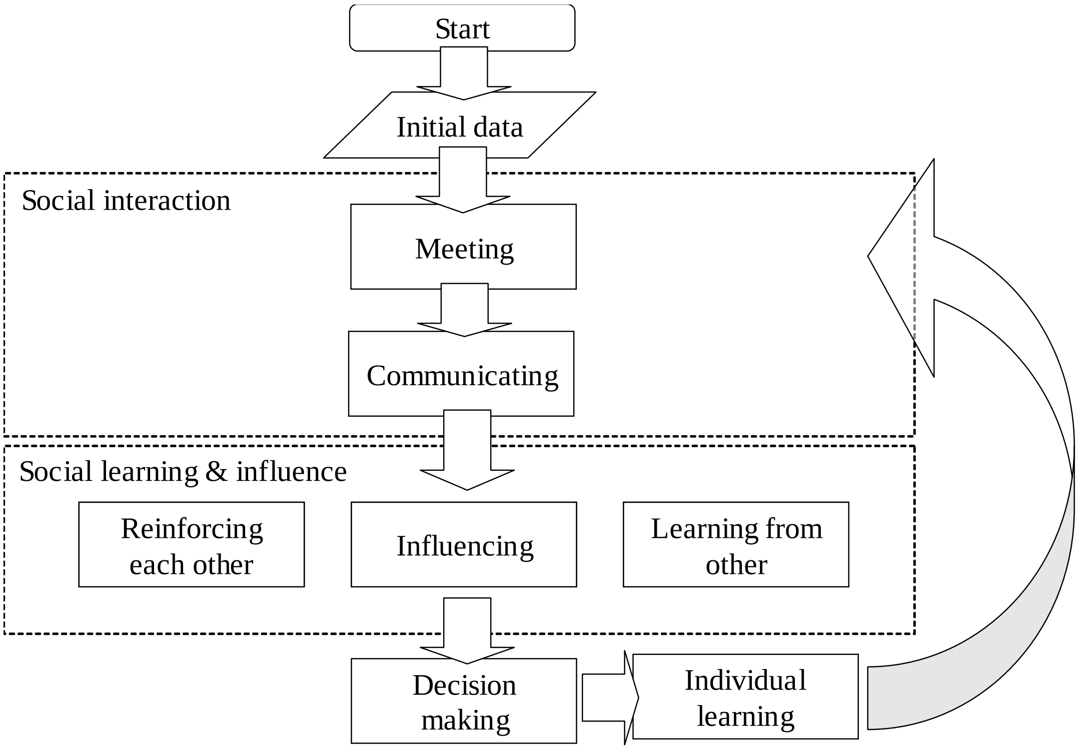

Figure X.1 Algorithm of the multi-agent simulation model

There are two types of agents: an influential agent (which is a member of the minority) and a common agent. An influential agent is given a higher *reputation score* than a common agent. The process of social learning and social influence may exist during a process of communication between two interacting agents. If both communicating agents have the same choice on a particular day then they are *reinforcing each other*. If they have different choices, there are two possibilities. First, if one of the communicating agents has a higher reputation than the other then the exchange of information will only be one way, from the agent with a higher reputation to the other with lower reputation. This is a process of *influencing the other*. Second, if they both have the same reputation, then only the agent who initiates the social interaction learns from his interaction partner's choice by updating its preference, since the initiator is considered as the one who is looking for information. This process is called a process of *learning from the other*.

The decision of whether to comply with a demand management measure is made based on the agent's preference value. Each agent learns individually from past decisions, learns/imitates other agents' decisions and is influenced by 'influential' individuals, and then updates his preference value in a reinforcement process. The higher the preference to comply is, the more the probability that the agent will comply with the measure. The decision making of each agent is based on a social influence model with each agent takes into consideration previous choices and choices of other agents. Please refer to Sunitiyoso et al. (2006) for detailed formulation of the model.

The decision making process of each agent is repeated from time to time. The population of agents also displays inertia, which means that they all may not change decisions at the same time. Some of them change their decisions but the others continue with their previous choices. And also each agent does not have perfect information about the choice of all other agents in the population. He only knows the choice of other agents whom he communicates with.

In the simulation model, a number of agents are generated and given attributes (parameters and initial variables) according to the attributes of respondents in the survey (see Sunitiyoso et al., 2006 for details). Since the number of respondents is limited (N=178), a technique so-called 'cloning' is used to produce a larger number agents (N_s =4096). This means that a number of agents are generated with similar attributes which come from the attributes of a respondent. So that approximately each respondent has 23 'clones' (N_s/N = 4096/178 ≈ 23) in the population of agents. Each simulation run has a period of T = 1460 days (4 years). The domains of interaction are *neighbourhood*, *courses of study*, and *non-study activity clubs*. There are eight scenarios used in the simulation runs. Each scenario is repeated for ten runs.

Table X.1 shows the results of six scenarios in the last 90 days of simulation runs. In Scenario 1, where social interaction between agents does not exist, the number of car sharers goes up gradually up to 2008 agents, which means the level of compliance (LC; the proportion of car-sharers in population) is 49.0%). When social interactions (in all domains of interactions: neighbourhood, course of study, and non-study activity club) exist between agents (Scenario 2), the number of car-sharers increases with a slower trend than in Scenario 1. However, the level of compliance in this scenario is higher than in Scenario 1 with 2290 car sharers (LC = 55.9%). The situation becomes better for car sharing when a number of influential minority agents (6.18% of total number of agents) exist in the population as seen in Scenario 3. These influential minority agents are able to increase the level of compliance up to in average of 2514 car sharers (LC = 61.4%).

Figure X.2 presents the results of Scenarios 1 to 3. These results represent the first 365 days (1 year) of simulation run, since the system is in equilibrium after that until the end of the run (1460 days = 4 years). Each point in the graph is an average of 10 simulation runs. Average preferences of agents (Figure X.3) in Scenarios 1 to 3 reach almost similar points to their levels of compliance (Figure X.2), since they are highly correlated based on the fact that the decision of each agent is made based on his preference.

Table X.1 Scenarios of simulation run based on existence and location of influential minority and social interaction domains

Scenario	Existence and location of influential minority	Interaction domain (neighbourhood, course of study, non-study social club)	% of car sharers (average of the last 90 days)
1	No	No social interaction	49.0
2	No	All domains	55.9
3	Yes, spread in population	All domains	61.4
4	Yes, spread in population	Neighbourhood only	55.9
5	Yes, spread in population	Course of study only	58.5
6	Yes, spread in population	Social club only	55.8

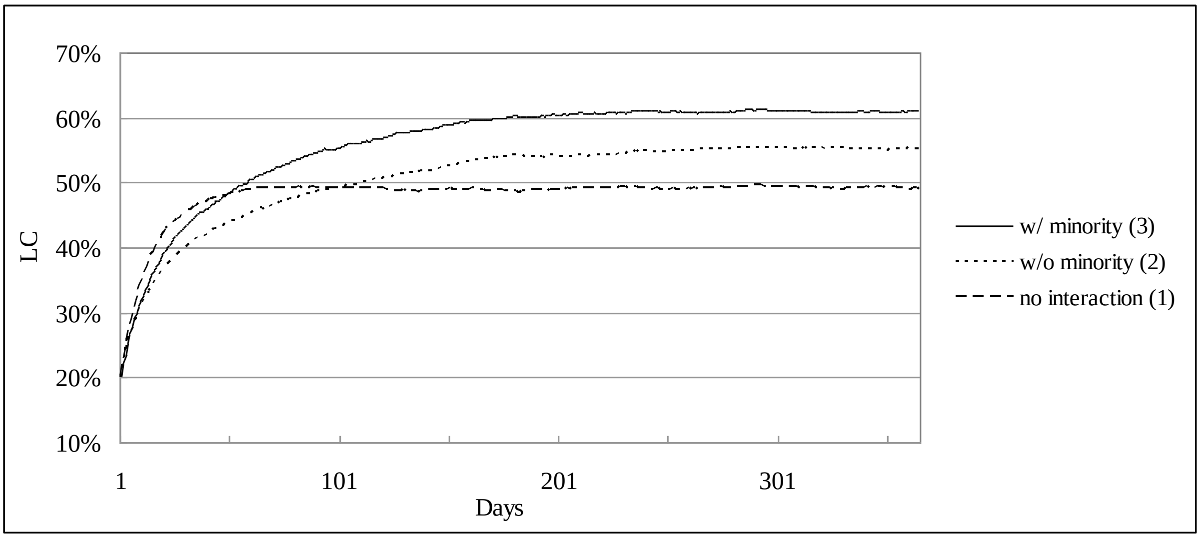

Figure X.2 Level of compliance (LC) in Scenarios 1 to 3 (Note: scenario numbers in parentheses)

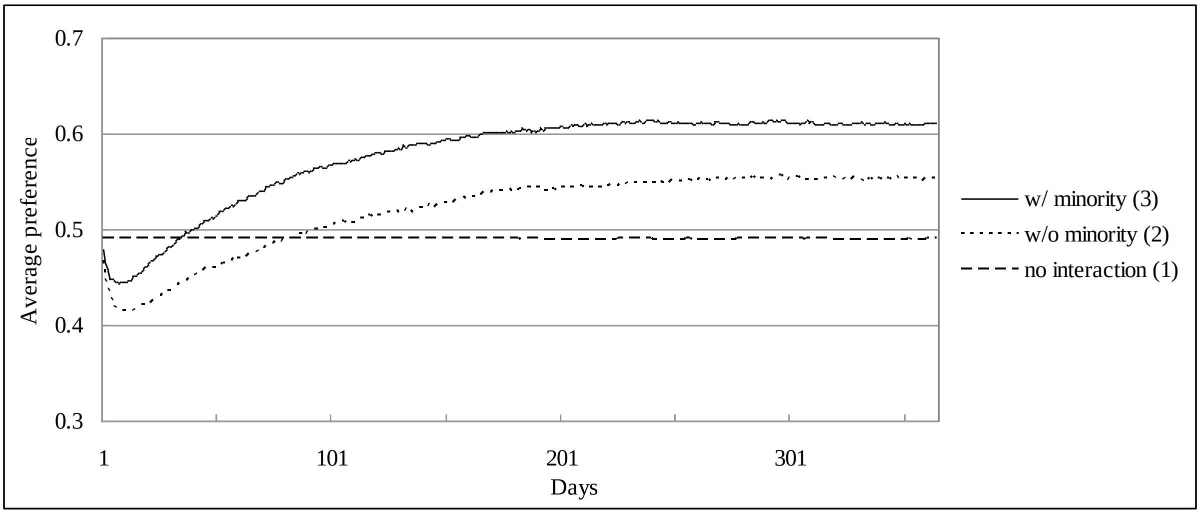

Figure X.3 Average preferences to car-sharing in Scenarios 1 to 3

In Scenario 1, where social interaction does not exist, the average of preference is stable day to day with an average of 0.49 in the last 90 days of simulation runs. This result is close to the initial average preference based on survey results, which is 0.47. Scenarios 2 and 3 have similar patterns of changes. In early interactions, average preferences in these scenarios decrease since a majority of agents, who have low preferences to car-share, decide not to car share causing the decrease of average preference. After the effects of initial conditions can be minimized, as agents involve in interactions with each other, the average preferences in Scenarios 2 and 3 increase higher than that of Scenario 1. These processes show an adaptation where travellers make decisions to initiate changes of preferences based on their own experiences and due to process of social interaction, social learning and social influence. Some travellers were influenced by other travellers but some were not. When influential minority agents are in charge, a higher level of compliance can be achieved in Scenario 3 (with minority) than that of Scenario 2 (without minority).

The effects of interaction domains are studied by comparing the system's behaviour whenever interactions happen in different sets of domains, as in Scenarios 3 to 6. Level of compliance has the highest level in Scenario 3 where all domains of interaction (neighbourhood, course of study and non-study activity club) are in use. It is followed by Scenario 5 where the domain is course of study, and then Scenario 4 (neighbourhood only) and Scenario 6 (non-study activity club).

To give an example of the dynamics of an agent's behaviour in the simulation, Figures X.4 and X.5 show the behaviour of an individual agent. Figure X.4 shows dynamic changes of an individual's preference during the first 100 rounds of a simulation run with Scenario 3. The changes are the results of the individual's experience as well as in the influence of other people's choice. The agent starts with an initial preference to car-sharing of 0.15 and by day 100, the preference reaches 0.5. Figure X.5 presents the agent's frequencies of activities in social interaction, learning and influence. It is shown that among the whole social interaction processes (*meeting* and *communicating*), there are some *meeting* processes which were not followed by *communicating* (exchanging idea). The process of *communicating* resulted in mostly in the processes called *reinforcing each other* and *learning from others*, and few occasions where the individual was being influenced by influential individuals (minority agents). This example is one of many patterns of behaviour that exist within agents in the simulation.

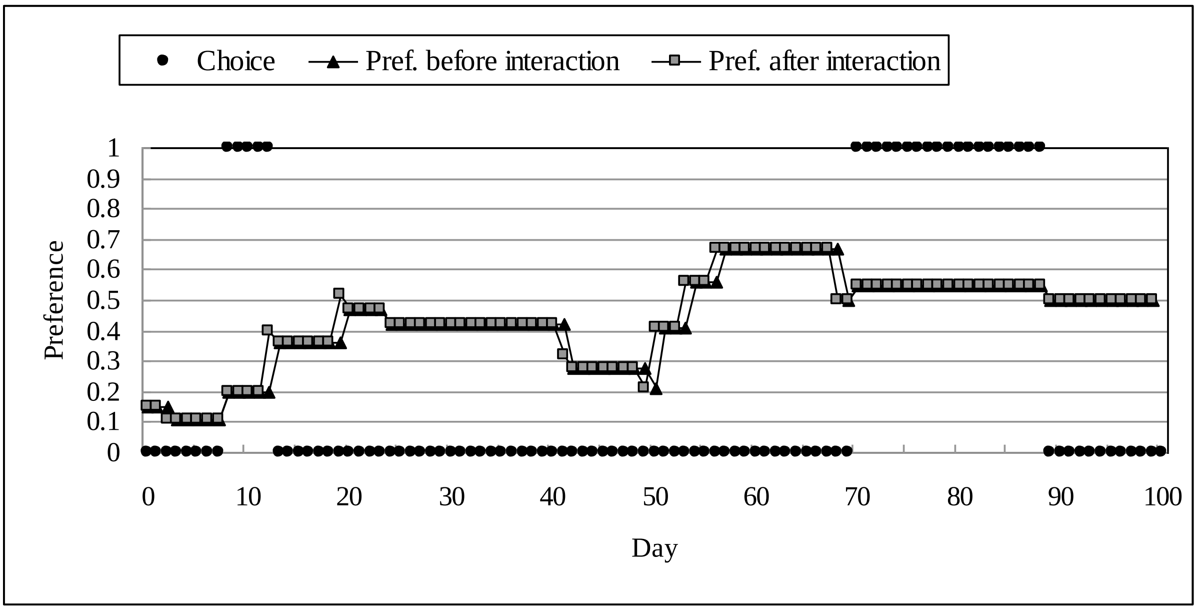

Figure X.4 Changes of an individual preference

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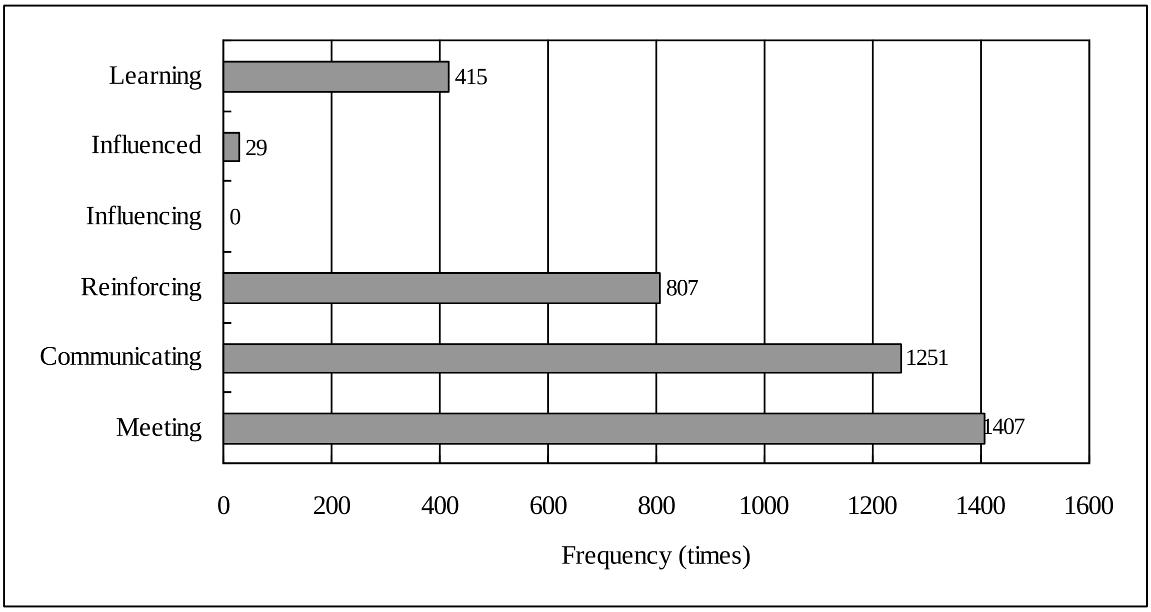

Figure X.5 Frequency of activities in social interaction, learning and influence over a full simulation run (T=1460 days)

Behavioural insights

The simulation experiment described in the example provides some behavioural insights regarding the influence of social aspects on travellers' behaviour during the diffusion process of compliance with a demand measure. It is revealed that social interactions between individuals helps diffusing the information between them through various interaction domains ('social club'), such as neighbourhood, workplace, school, community, and activity club, thus increasing the level of compliance to a demand management measure. Repeated interactions between individuals would generate high propensity for communicating which later give more opportunity for social learning and social influence to induce compliance in the population. Higher level of compliance (participation) with the measure is then produced with the support of 'minority' agents who are able to strongly influence other travellers' behaviour through various social interaction domains. Neighbourhood is a domain which has often been used in existing simulation models, however it may have smaller role than other 'social' clubs where interactions occur more often (e.g. school, workplace) since the interactions between neighbours, particularly in an urbanized city, are incidental and not as frequent as, for example, interactions within students in a school or university.

The insights support empirical findings of the role of *word-of-mouth* communication as a tool for diffusion. Ampt (2003) reported that in voluntary behaviour change projects messages delivered by any other way are reinforcing, but much less efficient. When the behaviour change has had a positive benefit to the individual it is likely that they will tell others of the benefits. Since they are more likely to practise diffusion in the company of trusted others, the message is more likely to lead to further change. Taniguchi and Fujii (2007) in their study of promoting community bus service found that word-of-mouth advertising through recommendations to friends and family plays an important role in promoting bus use. Spreading information by 'word-of-mouth' may help solving a concern stated by Cairns et al. (2004) about the implementation of personalised travel planning. They stated that the effects may be short-lived, if people may quickly slide back into their old travel habits once the monitoring is over. A laboratory experiment conducted to study the effect of communication on travellers' behaviour (Sunitiyoso et al., 2007) found that communication does influence their behaviour, although the effects are not consistent for different groups of individuals.

The simulation model also shows how travellers' behaviours 'evolve' over a long period of time when travellers interact with other travellers. This shows the important to study the dynamic not only in short-term but also in long term. Cairns et al. (2004) reveals the need to study the dynamic build-up of effects over time during the implementation of soft measures Empirical research has shown that the long-term effect of policy interventions (e.g., Goodwin, 1992) can be much stronger than the short-term effect. The same holds true for possible negative side effects which often occur in the long term.

It can be inferred from the example that involving 'key people', which were represented as influential minority agents in the model, in diffusing compliance with the measure into population would increase the level of participation. Identifying the influential individuals (the minority) is as important as involving them in promoting changes of behaviour using their influence. An influential individual is not necessarily a traditional leader, but he can be a 'trusted person' with a respected reputation in the social club as individuals are more willing to hear from someone who is trusted and respected as a consistent person. For example: a suggestion to car share by a consistent car sharer, who has been car sharing regularly in a considerable period of time, would have more influence than that of other individuals' who have not done so. In practice, the minority could be some opinion leaders and credible sources who are drawn from the community and trained to do so. These influential people have a 'minority' influence which is strong in influencing change of behaviour of other people even though they are small in number. They can help people overcome barriers to action and give ongoing support beyond their households. Jones and Sloman (2003) added the importance of involving key employees in the relevant organisations, so that they are aware of and supportive of the campaign in their dealings with members of the public.

In general, the study provides useful information for investigating the role of minority influence in the diffusion process of compliance with a soft policy measure. Some informed insights regarding the spread of compliance with a soft measure from an individual to other individuals through various kinds of interaction domain are obtained. The results are produced by self-organization and complex interaction processes between travellers in the system.

X.5 Conclusions

The study demonstrates the potential of utilizing a multi-agent simulation model to simulate the effects of social aspects, particularly social interaction, social learning and social influence, on the diffusion process of travellers' compliance with a demand management measure, which in this study is a car-sharing program. The model is also able to show the 'evolution' of behaviour over time and to demonstrate how agents can be equipped with decision rules that are based on social-psychological theory of social interaction, learning and influence and experimented with different settings. It has been indicated that the diffusion process of compliance with a demand management measure may depend on the way a traveller interacts with others (social interaction), the way he learns socially (social learning), and the existence of influential people (social influence) who strongly influence other people.

We may consider that the findings produced by the study are more in 'qualitative' rather than 'quantitative' sense, since they are used to explore or to understand theoretically the causal relationships of interaction between people which underlie the real world society rather than to represent societal dynamics in a precise way. Much elaboration is needed to produce sufficient sensitivity and accuracy in order to ensure that the findings are substantially important. The insights obtained from the simulation model in the example may be useful for understanding and finding possibilities for influencing travellers' change of behaviour during the implementation of a demand management measure. For example, the simulation shows that involving 'key people', represented as influential minority agents in the model, in diffusing compliance with the measure into population would increase the level of participation.

Before making use of a simulation model in real-world application, it is important to have credible parameters for the model which can be obtained from an intensive behavioural survey or laboratory-based experiments with people. A synergetic combination between empirical research and simulation research would yield benefits in our research. In this study, empirical data collected from a longitudinal study, which is a research study that involves repeated observations of the same subjects over long periods of time (e.g. months, years or decades), with several waves before and after the implementation of a soft measure would serve best for supporting the findings of a multi-agent simulation model.

In studying the effects of a treatment/intervention on individuals, a simulation experiment is able to handle the interactions of a large number of individuals with each other and with the transport system. The multi-agent simulation model described in this work highlights the potential results of social interactions of a large number of individuals in making a choice whether to participate in a travel demand management measure and shows how the interactions affect the overall system behaviour as well as individual behaviour. Behavioural changes in a wider societal scope are expected to differ from those of a smaller group of individuals, since interdependence between individuals becomes complicated whenever the number of interacting individuals increases. Dealing with this situation, the ability of a multi-agent model to handle a complex form of interactions becomes a major advantage. With agent-based simulation, it is possible not only to model the dynamics of the system but also to represent behavioural change of every single individual; therefore, it may become a powerful approach in understanding and predicting travellers' change of behaviour.

It also makes possible for conducting a large number of repetitions (time periods), which enable the researcher to observe whether individuals' choices converge to an equilibrium point or not, how they converge and the dynamics before convergence, and how many repetitions are required. Many patterns of change within travellers' behaviour during the implementation of a demand management measure can be observed in a multi-agent simulation. This may help transport planners in anticipating the potential effects of the measures at individual level.

The capability of multi-agent simulation for predicting potential travellers' behaviour in different scenarios or parametric conditions which resemble scenarios of a potential travel demand management measure in order to gain informed insights of how travellers would respond to each scenario. The insights could later be useful in designing demand measures that are potentially effective in changing travellers' behaviour. For example by incorporating social interactions and taking into consideration their potential effects into the design of transport measures (e.g. behavioural change programmes, user communication feature of ATIS).

We believe that the agent-based approach presented in this work provides a first step towards the creation of a novel tool for use by transport researchers and practitioners that can be incorporated in travel plans and other demand management measures.

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