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Generalized behavioral framework for choice models of social influence: Behavioral and data concerns in travel behavior

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ABSTRACT

Over the past two decades, transportation has begun a shift from an individual focus to a social focus. Accordingly, discrete choice models have begun to integrate social context into its framework. Social influence, the process of having one's behavior be affected by others, has been one approach to this integration. This paper provides a review and discussion of the incorporation of social influence into discrete choice models with specific application in travel behavior analysis. The discussion begins with a generalized framework to describe choice models of social influence. This framework focuses on the behavioral microfoundations of social influence and choice by separating the social influence mechanism from the source of its influence and by explicitly acknowledging the role of the social network in the model structure. This contrasts with prior work that focused on the measurement of contextual, endogenous, and correlated effects. Then, the state of the art in travel behavior research is reviewed using a taxonomy based on the generalized framework with research performed in sociology, social psychology, and social network analysis. The discussion then shifts to the importance of understanding the motivations for social influence, and the formation and structure of social networks are explored. Additionally, the challenges of collecting data for social influence studies are mentioned and the paper concludes with a look at the challenges in the field and areas for future research.

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1. Introduction

Travel is an integral part of peoples' lives which connects their residences and neighborhoods, work and economic opportunities, and geographical points of reference such as school, childcare, shopping, healthcare, and leisure. Increasingly, transportation researchers have become interested in the role of social interactions between people in a given individual's travel behavior (Dugundji et al., 2008, 2011a, 2012). Borrowing from the field of economics (Durlauf and Ioannides, 2010), social interactions are defined as "direct interdependences in preferences, constraints, and beliefs of individuals, which impose a social structure on individual decisions" (p. 452).

Within travel behavior research, the literature on social interactions is becoming relatively well-established. But recently, there has been growing interest in decisions involving social influence.[1] Social influence deals with how an individual's decision making process is altered by others' actions, behavior, attitudes, and beliefs of others (and the individual's perceptions of these). Of particular interest is the analysis of models in which the decisions of others are incorporated into discrete choice models. Since travel may involve different types of social influence from peers, family, neighbors, colleagues, and even society at large, incorporating these social effects into discrete choice models is non-trivial. These models are grounded in theories of individual choice of independent decision makers. Additionally, they are generally estimated on cross-sectional, choice-based data sources which make it difficult to identify social influence effects and their motivations. These motivations are important for understanding long-run behavior and for guiding organizations on appropriate intervention strategies to encourage behavioral change.

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[1] The more established area of social interactions in travel involves *social cooperation* which deals with active coordination of travel and activities. This generally involves intrahousehold and interhousehold planning and activity scheduling (Arentze and Timmermans, 2008; Van den Berg et al., 2010, 2012; Carrasco and Miller, 2006, 2009; Habib et al., 2008; Habib and Carrasco, 2011).

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The incorporation of social networks, the types and timing of interactions, and how social networks and interactions interface in spatial dimensions are difficult to model and identify from current data sources. Social influence models use a wide variety of network structures, varying from cliques to sparse networks, and the connections made can be due to similarity in social standing and interests and spatial proximity. Individuals' networks are also bounded by limitations in cognitive effort, time, and space. The spatial dimension of social networks is still an open research field and its use in transport models of social influence has been limited both in its actual application and its simplicity.

With an emphasis on behavioral and data issues, this paper aims to provide a behavioral framework for describing choice model approaches for decisions involving social influence. The paper begins with a quick example of how a simple hypothesis can be explained by various social and non-social factors. In Section 3, a generalized behavioral framework for choice models of social influence is introduced. Section 4 describes past research in travel behavior using this framework and describes the shortcomings in current models in the need to understand the motivations behind social influence. Sections 5–7 describe the framework's components of social network, social influence mechanism, and influence sources. Section 5 summarizes recent research on the types, motivations, and tactics of social influence. Section 6 describes the behavioral processes behind social network formation and common structural forms and Section 7 summarizes procedures for gathering social influence and social network data. The paper concludes with a summary and areas for future research.

2. A hypothetical example

To clarify the concept of social influence in modeling, we begin this section with a hypothetical, illustrative example of various sources of influence in travel behavior.

Suppose a researcher studying cycling behavior among students and non-students makes the following observation:

College students in the US are more likely to use a bicycle than non-students.

This simple observation could have various causes. The following are several possible explanations for this observation (observability is in reference to the modeler):

1. College students tend to live on college campuses which often have amenities that are nearby. Therefore, more student trips are within the comfortable range for bike travel compared to non-student trips. Individual-level differences in travel distance and trip time (Dickinson et al., 2003) may explain differences in cycling behavior between students and non-students. These variables are typically observable to modelers [**Observed individual-level effects**].
2. Cycling decisions depend on the choices of others because of social norms and conformity (Dill and Voros, 2007). This can cause a self-perpetuating cycle of low cycling rates in neighborhoods with non-students and high cycling rates in neighborhoods with students. For example, this can lead to a situation whereby once a few people start cycling, a critical mass is reached, and cycling becomes more popular [**Endogenous social influence effects – Conformity**].
3. Preferences for automobiles may be higher among lower income individuals compared to higher income individuals (Parkin et al., 2007). Higher income individuals have higher bicycle ownership and tend to cycle more often than lower income individuals. This may induce students to perceive cycling more favorably, perhaps more favorably than would be expected by income alone due to social norms [**Contextual social influence effects – Compliance**].
4. Environmentally-friendly individuals are more likely to cycle than others (Hunecke et al., 2001). If college campuses expose students to environmentally friendly views more frequently than non-students, this may lead to higher cycling rates among students (Haustein et al., 2009). Here, an institutional environment may cause an increase in student cycling rates [**Correlated environmental effects**].
5. Since cycling is a physical activity, a certain level of physical ability and health is needed to cycle. College students in the US tend to be less obese than non-students (Fowler-Brown et al., 2009) and since obesity correlates with health, this could explain a disparity in cycling rates. Since travel surveys tend to not measure health and ability, this may be an example of an unobservable effect which acts at the individual level [**Correlated individual-level effects**].
6. Schools may create a stronger sense of community than an average community so the strong cohesiveness of the social networks among students may allow quicker, stronger, and self-reinforcing dissemination of cycling behavior (Páez and Whalen, 2010) as compared to the less cohesive networks in communities outside of schools [**Social network structure**].

Each of these possible explanations requires a different policy intervention. For example, explanation #1 suggests that increasing the amenities in less dense areas would increase cycling rates, whereas explanation #2 suggests that investments in encouraging a few people to cycle (e.g. advertising campaign, bicycle loan program) would be more effective. Therefore it is critical to ensure that models correctly differentiate these effects, particularly for policy analysis.

3. Generalized framework for choice models of social influence

Conceptually, Manski (1993, 1995) outlines three different ways in which similarities in group behavior can be explained in a model, namely[2]:

- **Endogenous Social Influence Effects**, "*wherein the propensity of an individual to behave in some way varies with the prevalence of that behavior in the group*";
- **Contextual Social Influence Effects**, "*wherein the propensity of an individual to behave in some way varies with the distribution of exogenous background characteristics in the group*"; and
- **Correlated Individual-level and Correlated Environmental Effects**, "*wherein individuals in the same group tend to behave similarly because they face similar institutional environments [(environmental)] or have similar unobserved individual characteristics [(individual-level)]*".

Endogenous and contextual social influence effects characterize the relevance of group level behavior and group level characteristics respectively for individual behavior. An important distinction between these two specifications however, is that endogenous social influence effects allow for the possibility of direct feedback between individual behavior and group level behavior. Thus, endogenous effects can potentially be reinforcing over the course of time. Contextual social influence effects, while social, are presumed (at least short-term) not to involve direct behavioral

[2] Manski refers to these effects respectively as endogenous, contextual, and correlated effects, but they are renamed here to maintain consistency with the rest of the text.

feedback between the individual and others. In contrast, correlated individual-level and correlated environmental effects are presumed to be entirely non-social. This distinction between the different sources of similar group behavior forms the basis of the framework described in Section 3.1.

3.1. Framework description

The framework described in this paper approaches the subject from a behavioral perspective rather than through a measurement perspective. Discrete choice models lend themselves well to linking behavioral theory and statistical modeling (Durlauf and Ioannides, 2010). This is particularly due to the latent variable derivation of the payoff which can represent a theoretical quantity that can be minimized, maximized, or subjected to some other rule.

The framework rests on the assumption that the individual makes choices according to a decision rule that depends on evaluating payoffs. These payoffs depend on aspects specific to the individual and aspects of the social systems (actual or perceived) surrounding the individual. The backbone of the framework is the traditional discrete choice model with its focus on *individual-level effects* and *environmental factors* generated from individual characteristics and properties of the individual's environment, respectively. Individual-level characteristics, environmental factors, and non-choice related social factors (i.e. exogenous influence sources) are assumed to be exogenous to the individual's decision process.

Individuals are connected to one another through the *social networks* in their lives. These networks, which may have structures formed by self-selection due to individual characteristics, provide a reference to society through which social influence occurs. *Social influence effects* are a function of an individual's social networks. This is an important part of this framework, as it is an explicit acknowledgment of the importance of the social network. Different social networks may imply the use of different social influence mechanisms as well as different influence sources – endogenous or exogenous. Different choice contexts may imply the use of different social networks, e.g. mode choice may imply the use of co-worker networks whereas social trips would use friendship networks. Additionally, social networks can vary between individuals in their structure and the relationships between individuals.

When environmental factors and individual characteristics are correlated with an individual's social network (i.e. an individual's social contacts share the same environment or have similar unobserved characteristics), they become *correlated environmental and individual-level effects*, respectively. These factors can seem social when measured but truly are behaviorally non-social. A similar correlation can occur between influence sources and social networks. This can manifest through homophily of behaviors, attitudes, and values where individuals are connected to each other because they prefer to be around similar others.

From the combination of individual-level, environmental-level, and social influence effects, individual n obtains some payoff $\mathscr{P}_{ni}$ when choosing an alternative i. Assuming a linear-in-parameter form, the payoff function takes the following form:

$$\mathscr{P}_{ni} = \beta_i x_{ni} + \theta_i s_{ni}\big(G_n(w), m_{ni}(N), m^*_{ni}(N)\big) + \mu_i E_n + \varepsilon_{ni} \tag{1}$$

where

x_{ni} = individual-level characteristics of individual n for alternative i,
$s_{ni}(\cdot)$ = social influence mechanisms for individual n for alternative i due to endogenous and contextual factors,
$G_n(w)$ = individual n's social contacts and the strength of these relationships (modeled through a weighting function w),
$m_{ni}(N)$ = exogenous social influence sources of the population on individual n for alternative i,
$m^*_{ni}(N)$ = endogenous social influence sources of the population on individual n for alternative i,
N = the population of all individuals,
E_n = environmental factors on individual n (may include correlated environmental factors),
ε_{ni} = unobserved effects on individual n for alternative i (includes correlated individual-level effects and alternative-specific unobservables),
β_i, θ_i, μ_i = model parameters (these can be alternative-specific).

The individual chooses an alternative by evaluating the payoffs from each alternative according to a decision rule, $d(\mathscr{P}_{ni}, \forall i) \rightarrow y_n$. Fig. 1 summarizes the framework's components and interactions.

3.2. Comparisons to prior work

The framework in this paper provides a behavioral, microfoundations basis for social influence choice models. Previous work defined endogenous and contextual effects only "in terms of [the] types of variables rather than via particular mechanisms" (Blume et al., 2011, p. 941). The framework contrasts with previous works which classified on structural terms such as Manski's initial work (1993, 1995) on linear models which was primarily concerned with conformity[3] based on actual behavior. It also contrasts with Brock and Durlauf's (2001, 2002, 2006, 2007) extension to binary and multinomial choice models of conformity based on perceptions of behavior and rational expectations with complete information. The framework in this paper emphasizes this behavioral focus in contrast with the measurement focus by:

1. Explicitly mentioning the importance of social networks and its part as a function of social influence processes.
2. Consolidating endogenous and contextual social effects into a single concept of a social influence mechanism which depends on endogenous and exogenous influence sources respectively.
3. Generalizing influence sources beyond observed or perceived choices.
4. Allowing for heterogeneity in social influence and social networks (Roy et al., 2012) since both may vary depending on characteristics of the individual.
5. Generalizing the decision rule space beyond utility maximization.

4. State of the art in transportation

Travel behavior research analyzes social influence through applied inferential analyses, agent-based simulations, and experiments. The primary behavioral paradigm in discrete choice models of transportation is random utility maximization where an individual chooses the alternative which gives that individual the most utility. Two forms of social influence mechanisms have been used in travel behavior models: conformity (an endogenous social influence mechanism) and compliance (a contextual social influence mechanism). These models have the following form for the utility U_{ni} an individual n obtains from choosing alternative i and a utility maximizing decision rule[4]:

[3] Conformity is a social influence type where the actual behavior of others affects an individual's choice. Conformity is described in more detail in Section 5.1.

[4] In Eq. (2), $\theta_i s_{ni}(\cdot)$ is expanded as the summation of the contextual and endogenous social influence effects. Additionally, observed environmental effects are included here, but models in transportation generally ignore correlated environmental effects due to identification issues in cross-sectional models (Brock and Durlauf, 2007).

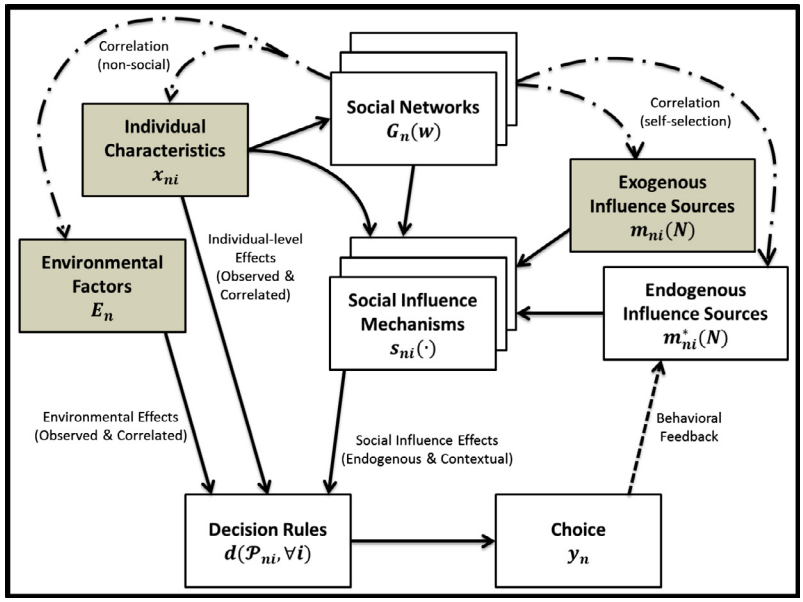

Fig. 1. Generalized behavioral framework for choice models of social influence. Note: Gray boxes refer to objects which are exogenous to the decision making process. Dot-dash lines represent possible correlations and dashed lines represent feedback effects.

$$U_{ni} = \beta_i x_{ni} + \mu_i E_n + \gamma_i k_{ni}(G_n(w), m_{ni}(N)) + \delta_i l_{ni}(G_n(w), m^*_{ni}(N)) + \varepsilon_{ni}$$
$$y_{ni} = \begin{cases} 1 & \text{if } U_{ni} = \max_{j \in C} U_{nj} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where

$k_{ni}(\cdot)$ = contextual social influence mechanism for individual n for alternative i,

$l_{ni}(\cdot)$ = endogenous social influence mechanism for individual n for alternative i,

$\beta_i, \mu_i, \gamma_i, \delta_i$ = model parameters (these can be alternative-specific).

4.1. Specific works in transportation

Applying the generalized framework to prior work provides a taxonomy for describing social influence models of discrete choice. Table 1 summarizes social influence models used in studies of travel behavior. Each model is classified according to the social networks, social influence mechanism and sources, and decision rule used in the study. From this classification, patterns emerge from the prior research. Social influence models in transportation are primarily models of conformity rooted in utility maximization. The modelers tend to use social network structures that are either: (1) large cliques of individuals joined by similar demographics or spatial proximity or (2) sparse networks of intimate social connections. Since data collection tends to be cross-sectional, influence sources generally are based on current behavior and are from in-sample connections. Few studies elicit data from the respondent on their social networks and the behavior of these social contacts nor do they get information directly from their social contacts.

4.2. Discrete choice models of conformity

As shown in Table 1, conformity is the primary social influence mechanism modeled in transportation. An individual conforms when that individual desires to change their own behavior to that of another person or persons (Cialdini and Goldstein, 2004). Since the behavior of others may be correlated through unobservable factors and simultaneity, conformity is considered an endogenous social influence mechanism. The use of conformity in travel studies is a simple extension of previous methods because it requires no additional data collection, since choice data is often collected in travel studies. Individuals also tend to be able to observe the choices of those closest to them and (sometimes) the publicly made choices from people outside of their direct social contacts. Therefore, an individual may have perceptions of the choices of people with similar social standing although they may not have intimate relationships with these individuals. This is also a weakness since these perceptions may be biased because individuals have limited information (e.g. extrapolations from limited observations, media bias) and limited cognitive abilities (Thaler and Sunstein, 2008).

Due to the cross-sectional nature of most travel surveys, most conformity models use an endogenous influence source based on the current behavior of peers. Most of these models use the following form to represent the utility observed for an alternative i during the current time period t:

$$U^{(t)}_{ni} = \beta x^{(t)}_{ni} + \delta \sum_{q \in g(n)} \frac{y^{(t)}_{qi}}{|g(n)|} + \varepsilon^{(t)}_{ni} \tag{3}$$

where

$U^{(t)}_{ni}$ = the utility an individual n obtains from choosing alternative i in the current time period t,

$y^{(t)}_{qi}$ = 1 if individual q chose alternative i in time period t; 0 otherwise,

$q \in g(n)$ = an individual q in individual n's social contacts,

$|g(n)|$ = the number of individuals in individual n's group of social contacts,

$\varepsilon^{(t)}_{ni}$ = unobserved individual-level effects in time period t for alternative i (can include individual-level correlated effects).

This form assumes a direct-benefit effect is generated from conforming to the behavior of others (i.e. utility is directly increased by conforming). But conformity is not always generated by the same motivation; the question of why are people conforming often is not being answered. Are individuals transferring information? Are people envious of others and aspiring to obtain a similar status? Is this just a fad? These motivations have important

Table 1
Discrete choice models of social influence in travel behavior research.

Paper authors	Application area	Social network	Social influence mechanism	Influence sources	Decision rule (model type)
Abou-Zeid and Ben-Akiva (2011)	Mode choice	An acquaintance (respondent-reported) with a similar commute	Conformity (social comparison)	Current behavior and social comparison indicators	Utility maximization (hybrid choice model with latent variables)
Adjemian et al. (2010)	Vehicle ownership	Nearest neighbors based spatially within 8 km	Conformity	Past behavior/lagged behavior (in sample)	Utility maximization (binary logit)
Baltas and Saridakis (2013)	Vehicle type choice	Egocentric network of friends, relatives, & acquaintances; not explicitly measured	Compliance or conformity (informational)	Whether information was sought before purchase	Utility maximization (multinomial logit)
		Access to car TV shows, car literature, car salesmen, & brochures	Compliance (affect & arousal)	Whether information was sought before Purchase	
Dugundji (2012)	Mode choice	A large clique of everyone	Conformity	Current behavior (in sample)	Utility maximization (nested logit)
Dugundji and Gulyás (2003)	Theoretical	Random sparse networks (Poisson/Erdos–Renyi & Watts-Strogatz graphs)	Conformity (dynamical systems)	past behavior (from previous simulation timestep)	Utility maximization (binary logit)
Dugundji and Gulyás (2008)	Mode choice	[1] Large cliques based spatially on residential district	Conformity (dynamical systems)	Current behavior (in sample) & past behavior (from previous simulation timestep)	Utility maximization (multinomial logit; nested logit)
		[2] Large cliques based socially on age, income, & education	Conformity (dynamical systems)		
Dugundji and Gulyás (2012a)	Mode choice	Random sparse networks (Poisson/Erdos–Renyi graphs), equal probability of linking between all individuals	Conformity (dynamical systems)	Past behavior (from previous simulation timestep)	Utility maximization (binary logit)
Dugundji and Gulyás (2012b)	Mode choice	[1] Large cliques based spatially on residential district	Conformity (dynamical systems)	Current behavior (in sample) & past behavior (from previous simulation timestep)	Utility maximization (nested logit)
		[2] Large cliques based socially on age, income, & education	Conformity (dynamical systems)		
Dugundji and Gulyás (2013)	Mode choice	[1] Large cliques based spatially on residential district or postal code	Conformity (dynamical systems)	Current behavior (in sample) & past behavior (from previous simulation timestep)	Utility maximization (multinomial logit; nested logit)
		[2] Large cliques based socially on age, income, & education	Conformity (dynamical systems)		
Dugundji and Walker (2005)	Mode choice	[1] Large cliques based spatially on residential district or postal code	Conformity	Current behavior (in sample)	Utility maximization (mixed cross-nested logit)
		[2] Large cliques based socially on age, income, & education	Conformity	Current behavior (in sample)	
Fukuda and Morichi (2007)	Bicycle parking	Large clique based spatially on bicyclists who share a railway station	Conformity (normative, dynamical systems)	Current behavior (in sample)	Utility maximization (binary logit)
[A] Gaker et al. (2010)	Vehicle ownership	A directed four-mode network of temporally-lagged participants in an economics experiment	Conformity (information cascade)	Past behavior (in experiment)	Utility maximization (multinomial logit)
[B] Gaker et al. (2010)	Pedestrian crossing behavior	[1] Hypothetical source of State Law	Compliance (authority & obedience)	Shown current law (stated in choice experiment)	Utility maximization (multinomial logit)
		[2] Hypothetical source of citation rates and fine penalties	Compliance (authority & obedience)	Past actions (citation rates & fine amount, stated in choice experiment)	
		[3] Large clique of all University students & staff	Conformity (informational)	Past behavior (out of sample, stated in choice experiment)	
		[4] Hypothetical source of accident statistics	Compliance (affect and arousal)	Shown statistics (stated in choice experiment)	
Goetzke (2008)	Transit mode choice	Nearest sampled neighbors based spatially (⩽40 individuals within 1.2 km); weighted equally	Conformity	Current behavior (in sample)	Utility maximization (binary logit – conditional autoregressive)
Goetzke and Andrade (2010)	Walking mode choice	Nearest three sampled neighbors based spatially; weighted by spatial distance	Conformity	Current behavior (in sample)	Utility maximization (binary logit)
Goetzke and Rave (2011)	Bicycle mode choice	Large cliques based spatially on municipality	Conformity	Current behavior (in sample, instrumented)	Utility maximization (binary logit)

(*continued on next page*)

Table 1 (*continued*)

Paper authors	Application area	Social network	Social influence mechanism	Influence sources	Decision rule (model type)
Goetzke and Weinberger (2012)	Vehicle ownership	[1] Large cliques based spatially on census tract [2] Large cliques based spatially on census tract	Conformity Compliance (social norms)	Current behavior (from another dataset) Census-tract level education, income, & household size	Utility maximization (binary probit)
Grinblatt et al. (2008)	Vehicle ownership	Nearest sampled neighbors based spatially; weighted by distance ranking (1–500 neighbors placed in rings of varying sizes)	Conformity (informational)	Previous behavior (in sample)	Utility maximization (binary logit)
He et al. (2014)	Vehicle ownership	Random sparse networks with links probabilistically based socially on homophily	Conformity	Previous behavior (in sample & simulated)	Utility maximization (multinomial logit)
Kamargianni et al. (2014)	Mode to school choice	Parents of the adolescent student	Conformity and compliance	Parental walking-loving attitude (latent variable indicated through student's perception & parent's behavior)	Utility maximization (hybrid choice model with latent variables)
Kuwano et al. (2013)	Personal mobility ownership	[1] Egocentric network of friends [2] Hypothetical large cliques based on regions	Conformity Conformity	Current behavior (stated in choice experiment) Current behavior (stated in choice experiment)	Utility maximization (binary logit)
Kuwano et al. (2012)	Vehicle ownership	A hypothetical single large clique of vehicle buyers	Conformity (affected specific classes of individuals)	Current behavior (stated in choice experiment)	Utility maximization (latent class RUM)
Kuwano et al. (2011)	Vehicle ownership	[1] Large cliques based socially on income [2] Large cliques based spatially on neighborhood [3] A large clique representing a nation	Conformity Conformity Conformity	Current behavior (in sample) Current behavior (in sample) Current behavior (in sample)	Utility maximization (dynamic GEV)
Páez and Scott (2007)	Teleworking choice	Random sparse networks with links probabilistically based on homophily from a two-dimensional social lattice (9 networks generated)	Conformity (dynamical systems)	Past behavior (from previous simulation timestep)	Utility maximization (binary logit)
Páez et al. (2008)	Residential choice	Random sparse network with links probabilistically based on varying degree distributions & clustering (24 networks generated)	Conformity (dynamical systems)	Past behavior (from previous simulation timestep)	Utility maximization (multinomial logit)
[A] Pike (2014)	Mode choice	Egocentric network of up to five contacts (contacted within last six months)	Conformity	Current behavior (respondent reported)	Utility maximization (multinomial logit)
[B] Pike (2014)	Mode choice	Nearest neighbors based spatially ranging from within 250–25,000 feet	Conformity	Current behavior (in sample)	Utility maximization (multinomial logit)
Rasouli and Timmermans (2013a, 2013b), Kim et al. (2014)	Vehicle ownership	[1] Hypothetical egocentric network of friends & acquaintances, relatives, colleagues, & peers; not explicitly measured [2] Hypothetical public access to car reviews	Conformity Compliance (affect & arousal) or conformity (informational)	Current behavior (stated in choice experiment) Summary of review favorability (stated in choice experiment)	Utility maximization (binary logit with panel effects; mixed logit; Hybrid choice model with latent variables)
Scott et al. (2012)	Teleworking choice	[1] Egocentric network of co-workers with advice-seeking contact [2] Egocentric network of co-workers without advice-seeking contact	Conformity Conformity	Current behavior (respondent reported) Current behavior (respondent reported)	Utility maximization (multinomial probit)
Sidharthan et al. (2011)	Mode choice	A large clique of everyone; weighted inversely to spatial distance	Conformity	Current behavior (in sample)	Utility maximization (multinomial probit)
Walker et al. (2011)	Mode choice	[1] Large cliques based spatially on residential postal code [2] Large cliques based socially on income	Conformity Conformity	Current behavior (in sample) Current behavior (in sample)	Utility maximization (multinomial logit)
Wu et al. (2013)	Tourism participation	[1] Large cliques based spatially on prefecture [2] Large cliques based socially on occupation [3] Large cliques based socially on income	[a] Conformity [b] Compliance (social norms) Conformity Conformity	Current behavior (in sample) Prefecture-level education, household size, & household income Current behavior (in sample) Current behavior (in sample)	Utility maximization (mixed multinomial logit)

Note: Social networks are assumed to be undirected and weighted evenly between contacts unless otherwise stated.
Multiple entries from a single paper represent distinctively different models.
The terms in this table (e.g. compliance, clique, and egocentric network) are fully defined in Sections 5–7.
RUM = Random Utility Model, GEV = Generalized Extreme Value.

implications when the dynamical processes of behavior are analyzed – to determine the decision process between time periods and thus long-run behavior. Dynamical models in the literature[5] use the past behavior of peers as an endogenous influence source and typically use the following form:

$$U_{ni}^{(t)} = \beta x_{ni}^{(t)} + \delta \sum_{q \in g(n)} \frac{y_{qi}^{(t-1)}}{|g(n)|} + \varepsilon_{ni}^{(t)} \tag{4}$$

where

$y_{qi}^{(t-1)}$ = 1 if individual q chose alternative i in time period $t-1$; 0 otherwise

But this model specification is most relevant for behavior where imitating others provides direct benefits such as in popularity and status seeking. In contrast, if the conformity is informational, then perhaps the individual's choice set should change to include this new option or the attributes of the new alternative should increase in attractiveness.

The level of detail to determine the factors motivating the social influence process are lacking in the travel behavior field. With proper data and modeling techniques, a better understanding of social influence processes may be inferred. Grinblatt et al. (2008) presents an example with their thorough analysis of Finnish vehicle ownership study involving state-provided data on location and vehicle purchasing behavior. With an extensive dataset, varying model specifications, and descriptive statistics, they suggest that transfer of information is the most likely method of influence in their study. Additionally, they found that their results could possibly support conformity or status signaling but likely refutes hypotheses about individuals feeling envy toward other car owners.

The travel behavior field needs to place greater focus on the motivations and tactics behind the social influence process. In Section 5, some examples of the motivations for social influence are explored.

5. Social influence mechanism: Types, motivations, and tactics

In the social influence mechanisms component of the framework, social influence is represented by a mathematical formulation of $s_{ni}(\cdot)$. Social influence occurs through tactics that aim to satisfy the motivations of an individual. Social influence choice models can be enhanced by considering these interactions in the formulation of $s_{ni}(\cdot)$. Various social influence tactics have been studied extensively in the social sciences and a comprehensive introduction and review is beyond the scope of this paper. Kelman (1958) provides an early taxonomy to describe social influence through the types of compliance, identification, and internalization. Pratkanis (2007) describes 107 different social influence tactics classified by influence technique: landscaping, source credibility, convincing presentation, and emotional persuasion. Conformity, the most commonly modeled influence process in travel behavior, is too diffuse a mechanism to describe specific micro-level behavior. For example, conformity can be described by all three of Kelman's (1958) influence types.

This section classifies social influence along the lines of Cialdini and Goldstein (2004). Their review concentrates on late 1990s and early 2000s social influence literature which tended to look at "subtle, indirect, and nonconscious" sources of social influence. These are the processes most likely to be present at the data scales relevant for travel behavior research that uses discrete choice modeling. Cialdini and Goldstein (2004) separate social influence into the two types of *conformity* and *compliance*. Individuals are influenced when it serves their motivations for *accuracy*, *affiliation*, and/or *maintenance of a positive self-concept*. This classification closely parallels the generalized framework for social influence models of discrete choice and the majority of work in the travel behavior field.

5.1. Conformity

Individuals conform when they attempt to match the behavior of others. Thus, conformity parallels the discussion on endogenous social influence effects since the influence source is a function of the choices of others. Conformity can be informational or normative. Cialdini and Goldstein (2004) frame different research areas in conformity through the motivations of accuracy, affiliation, and maintenance of a positive self-concept. These social influence tactics are listed below:

- Accuracy
  - *Perceived Consensus*
  - *Dynamical Systems*
  - *Automatic Activation*
- Affiliation
  - *Behavioral Mimicry*
  - *Gaining Social Approval*
- Maintaining a Positive Self-Concept
  - *Majority & Minority Influence*
  - *Deindividuation Effects*

The model forms generally used for conformity can fit many motivations, but these motivations need different interventions to generate changes in the strength of social influence effects. For example, if influence is motivated by accuracy due to the tactic of *perceived consensus*, then changing behavior may involve exposing individuals to alternative behaviors in order to break the consensus perception.

The conformity modeled in the common model forms in Eqs. (3) and (4) introduce ambiguity in the identification of the influence mechanism. Often these models can be explained by all three motivations. For example, *perceived consensus* parallels the Brock and Durlauf (2001, 2002) model where social influence occurs through perceptions of the behavior of others, but they assume rational expectations which correspond with the actual average behavior.[6] Applied work in transportation has not measured behavioral perceptions. In *individual activation*, individuals minimize cognitive effort by imitating the actions of others. This technique may possibly be measured in social influence models if individual-level effects $\beta_i x_{ni}$ are approximately zero. For *gaining social approval*, individuals may imitate the actions of others in order to "restore their sense of belonging and their self-esteem" (Cialdini and Goldstein, 2004, p. 611). In *majority* influence, group members "[identify] with a message source" (p. 612) and may desire to signal to themselves and others that they are a member of said groups by exhibiting similar behavior. Deindividuation *effects* parallels research on the social identity approach (Reicher et al., 1995) and may present as a social norms-based influence where the norm is conveyed through the observed actions of similar others.

5.2. Compliance

In contrast with conformity, compliance draws parallels to contextual social influence. Influence sources come not from the

[5] See Table 1 for examples where social influence occurs through conformity via dynamical systems.

[6] Li and Lee (2009) counter the rational expectations assumption by using data that measured behavioral perceptions and Manski (2004) encourages the measurement of expectations.

individual seeing or perceiving the behavior of other but from advice, commands, and norms[7] that trigger specific behaviors. These triggers can be explicit (e.g. direct request from a supervisor) or implicit (e.g. an advertisement). For social influence through compliance, Cialdini and Goldstein (2004) mention a number of different social influence tactics for motivating compliance including:

- Accuracy
  - *Affect and arousal*
  - *That's-not-all technique*
  - *Resistance*
  - *Authority and obedience*
  - *Social norms*
- Affiliation
  - *Liking*
  - *Reciprocation*
  - *Door-in-the-face technique*
- Maintaining a Positive Self-Concept
  - *Foot-in-the-door technique*
  - *Consistency and commitment*

Compliance motivations have been limited in travel models of discrete choice and the specific tactics relevant to travel behavior will be described. S*ocial norms* are considered by Wu et al. (2013) and Goetzke and Weinberger (2012) by using exogenous influence sources. Social norms are "[rules that state] expectations about the appropriate and correct behavior in a situation" (Pratkanis, 2007, p. 38). *Authority and obedience* may be pertinent to work on the influence of authority figures at work and home, government and law enforcement (Gaker et al., 2010), and counter-culture elements. The *foot-in-the-door technique* is used often by individuals, groups, and institutions to encourage compliance by removing barriers to an option for a limited time, such as free transit days or bike-to-work days (Rose and Marfurt, 2007). In *consistency and commitment*, an individual may be motivated to perform behavior in accordance with a prior promise they made. The individual will attempt to maintain consistency with their self-concept. Cialdini and Goldstein (2004) note that this is more effective in individualistic societies compared to collectivist societies. *Affect and arousal* also has relevance due to advertising techniques. For example, automobile advertisements attempt to entice favorable emotions in their ads to compel individuals to change behavior (Baltas and Saridakis, 2013).

The motivation patterns of conformity and compliance work at different levels of social interactions and access different types of people that an individual may come into contact with. Thus, the social networks of the individual and the processes that form and shape those networks will have important implications on the effect of social influence in the decision process.

6. Social networks: Process and structure

In social influence processes, it is critically important to understand who transfers influence to an individual. Individuals are connected to each other through various means, such as through workplace, social media, and family relations. These linkages between individuals form a comprehensive social network, and the synergies between social networks and social influence need to be taken into account when modeling social influence.

In studies of social influence and diffusion, varying strains of research support and refute the hypotheses that influence occurs primarily due to: (1) personal influence between the direct contacts of an individual, (2) the influence of social groups, social circles, and social position, and (3) the influence of marketing and the media (Kadushin, 2012). Since each of these sources entails different social interactions, this translates into a critical connection between the social influence mechanism, the underlying social network, and the sources of influence. Thus, social influence hypotheses require different social networks to explain their behavioral processes correctly, such as:

- *Minority Influence*. In minority influence, individuals in a smaller group (the minority) may influence the behavior of members of the majority by appealing to a shared identity. Because of the importance of overlapping social circles to create shared identities, a network of close contacts as well as acquaintances would be an appropriate social network for studying minority influence.
- *Comparative Happiness*. In comparative happiness, individuals compare their current situation with that of a target peer. If there is a discrepancy, the individual may emulate the target peer to gain a more favorable condition. Because the cognitive costs of making comparisons are high, a social network with small, intimate connections would likely be most appropriate.
- *Authority and Obedience*. In authority and obedience (i.e. social power), an individual emulates the behavior of those with higher social position. Thus, a hierarchical social network showing roles in an organization and the directions of social power would be helpful.
- *Affect and Arousal*. In affect and arousal, a source attempts to appeal to the emotions of the individual in order to trigger favorable behavior. A possible network structure for this influence mechanism may include a bipartite network showing connections between individuals and advertising sources.

When the modeler is thinking about appropriate social networks for their analysis, it is critical to understand: (1) why connections are made and (2) what kind of network structures are appropriate/likely? This section describes factors that are important when formulating the social networks component of the generalized framework described in Section 3.1.

6.1. Link generation process

The question of why connections are made is critical for understanding the importance of social networks and their effect on social influence. Kadushin (2012) summarizes research showing that the three major motivational foundations of social networks are social safety, brokerage, and status.

Social safety is important in nourishing a sense of community (density), affiliation, and trust (Kadushin, 2002). Social networks typically provide this safety by linking individuals according to propinquity and homophily. Propinquity describes the increased likelihood of interacting with individuals who are located close to you spatially, while homophily describes how individuals tend to associate with others who are like themselves.

Propinquity,[8] most commonly in the form of spatial proximity, is a common basis for generating social networks in social influence models due to the ease of measuring spatial attributes (Dugundji and Walker, 2005). The open question remains of how to determine

[7] Norms may affect individuals through both conformity and compliance. In normative conformity, the norm is conveyed directly through the behavior of others. In compliance, other avenues of influence – such as advertisements, advice, commands, policies, laws, and ideal types – are used to convey the norm to an individual.

[8] Propinquity is more generalizable than just spatial proximity. It can refer to the ease of communication between individuals. For example, virtual propinquity can include ease of access via social media and text messaging. Thus, it is suggested that the term propinquity is used because of its generality.

what level of spatial aggregation is appropriate for different social influence types. While these spatial units may be appropriate for simple transportation planning purposes, physical distance has varying implications between different topologies and build environments, near-distances and very far-distances, and even between different individuals (Robins and Daraganova, 2013). Kowald et al. (2013) noted a tendency for individuals to have a majority of contacts within about an hour drive, while Matous et al. (2013) similarly found that, in an infrastructure-poor region, individuals had 95 percent of their contacts within a 90-min walk Although propinquity is common in social networks, it is not guaranteed that individuals connect with their neighbors. Indeed, some research finds that some neighborhoods are more cohesive than others and that even the transportation network can influence this cohesion (Grannis, 1998; Whalen et al., 2012).

Homophily describes how similar individuals are more likely to be connected to one another (McPherson et al., 2001). The importance of this has been briefly mentioned in the transportation literature (e.g. Dugundji and Walker, 2005; Kuwano et al., 2011; Wu et al., 2013). The general pattern is to choose socioeconomic indicators and place individuals into groups based on these categories. A contrasting approach involves quantitatively combining different aspects of an individual's socioeconomics into a measure of social similarity such as Blau space (Blau, 1977) or social distance (Akerlof, 1997).

The *brokerage* of different social groups and circles facilitates the human desire to explore the unknown. It aids in transferring knowledge, influence, and social capital between different parts of society and can give the individuals who link these parts power and status. In research on the adoption of electric vehicle technology, Axsen and Kurani (2012) and Axsen et al. (2013) mention the effect of brokers and the connections between social groups in transferring influence. For models emphasizing the diffusion of behavior through sparse networks, these connections are critically important to understand due to drastic changes in diffusion patterns and in the design of effective behavioral interventions.

Lastly, status entails a ranking of the power and prestige of individuals and comparisons thereof. Status can be created by organizational structures (e.g. job roles at work) and the allocation of resources (e.g. money, authority, social connections). This can encourage social interactions where individuals attempt to status seek – whether consciously or subconsciously – in order to maintain their status or seek higher status. For example, Wilton et al. (2011) mentions that, in semi-structured interviews, some employees expressed reservations about teleworking due to negative perceptions among their supervisors.

6.2. Network structure

The network structure is critically impacted by the link generation process and the form of social influence. From this structure, long-run impacts of social influence are affected. Social safety, effectance, and status seeking – the primary motivations for network formation – lead to the network structural properties of dense networks, structural holes and weak ties, and pyramid/hierarchical structures, respectively (Kadushin, 2002). These properties parallel some common network types that are used in research including cliques[9], small-world networks, and hierarchical networks. This section will briefly describe these network structures and concludes with a look at future development in spatial-social network overlays and two-mode networks.

A *clique* is a maximally dense section of a network where all individuals in the clique are connected to each other. When social networks are assumed to be reflexive large cliques, conformity models are commonly called field-effect or mean-effect models. Cliques are a good representation of small groups where it is easier to communicate with and observe the behavior of all group members. But this assumption becomes less behaviorally plausible as social group size increases since the individual is unlikely to know each person in his reference group and coordinating actions would be more difficult[10]. On the other hand, larger group sizes allow for estimates of choice percentages that are more robust to the influence of any one particular individual. Therefore, care must be undertaken when using clique structures, and modelers need to be clear about their motivations for and the limitations of using this structure.

The existence of small-worlds in human social networks is attributed to the small-world experiment (Milgram, 1967) which led to the "six degrees of separation" concept. *Small-world networks* are sparse networks that exhibit high clustering and short average path lengths. Thus, individuals tend to form relationships such that (1) an individual's friends tend to be friends with each other but (2) "social network [also] tend to have very short paths between essentially arbitrary pairs of people" (Easley and Kleinberg, 2010, p. 32). Small-world networks are commonly viewed as due to assortative mixing (Newman and Park, 2003) or preferential attachment. In assortative mixing, individuals with many social connections are attracted to other highly-connected individuals. In preferential attachment, these highly-connected individuals are not more attracted to one another, but tend to connect to low-degree nodes in the network. This is a difficulty with using small-world networks; they are sufficiently broad that researchers do not always understand which process formed them.

Hierarchical structures are generally directed social networks where influence flows from those with higher status or power to individuals with less. These commonly come in the form of status, role, or authority networks such as the example of a workplace network in Fig. 2. This directed nature of the influence contrasts with the clique and small-world structures mentioned before and has implications in studies of families, workplaces, small communities, and other organizations. With richer data sources and more research on social interactions of small groups, this network structure will be used more often travel studies.

Spatial-social network overlays refer to combining spatial features and social networks to realize the impact of geospatial factors on the structure of social networks. For example, in the spatial-social network shown in Fig. 2, there are few connections across the river due to the bridge's impact on travel and physical contact. Although some individuals are directly across the river from one another, they make contact with other individuals who are farther by Euclidean distance but located on the same river bank. This has implications on the formation of structural holes and weak ties in social networks – possibly leading to small-world networks (Wong et al., 2006) – and needs to be more thoroughly understood in the context of travel studies with social network data.

"A *two-mode network* [or bipartite network] consists of two sets of distinct units (e.g. people and events), and the relations that are measured between the two sets, e.g. participation of people in events" (Hennig et al., 2012, p. 50, emphasis added). This could be particularly relevant for situations where influence is not coming directly from direct connections between individuals but from shared events, perceptions, or influence sources. Sun et al. (2013) provides an example in which transit smart card data is used to create networks of individuals linked by the sharing of transit

[9] The nearest neighbor networks used in Goetzke (2008), Grinblatt et al. (2008), and Adjemian et al. (2010) are a similar conception but non-reflexive. This technique is a non-parametric technique that also creates dense networks with propinquity-driven link generation.

[10] An anonymous referee mentions the difficulty of coordinating and signaling average mode shares in large groups (see work by Brewer and Hensher (2000) and Murdoch et al. (2003)).

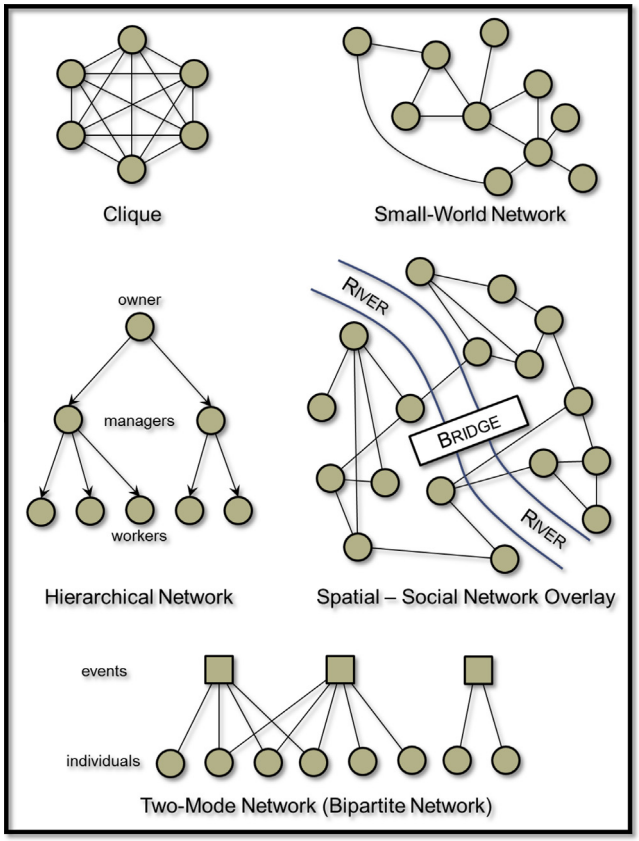

Fig. 2. Examples of network structures.

spaces during trips. Another example includes works deriving from the social identity perspective (Tajfel, 1978; Tajfel and Turner, 1979; Turner et al., 1987) where individuals in the same social category may share some ideal. This ideal type connects the individuals' behavior by serving as a prototype of expected behavior for group members (Akerlof and Kranton, 2000).

7. Data collection for social influence, networks, and sources

With a clearer idea of the influence mechanisms and the social network structures likely, modelers are faced with the task of collecting data to determine the mechanisms and sources of social influence and the social network connections for their specific application. Kadushin (2012) notes the lack of "large-scale true social-interaction-network data" as a common problem across many fields. Travel behavior research is not immune from this issue as there have been limited studies collecting social network data linked with travel data (Kowald et al., 2013). Section 7.1 begins by noting the limitations of choice-data approaches. Section 7.2 explains how qualitative data can be used to guide model formation, and then Section 7.3 looks at direct survey and experimental approaches for collection social data. Section 7.4 concludes with a discussion of stochastic network models which can be used for exploratory research or when survey methods are costly, difficult, or prohibited.

7.1. Choice-data approaches

Modelers face the major problem that identifying social networks from choice-data only is difficult. Often, modelers use large cliques and take group membership as given. Support is often based on convenience and data limitations rather than evidence. Walker et al. (2011) note concerns with their spatial group definitions due to data limitations and issues with the modifiable area unit problem and sharp spatial boundaries (Páez and Scott, 2004). Goetzke's (2008) study of transit mode choice limited social networks to the closest 40 neighbors, stating that increasing the network size would not significantly impact average mode share.

Inferring group membership from data is a possible answer but modelers must be cautious with their conclusions. Manski (1993) shows for linear-in-means models that using individual-level characteristics to determine group memberships – i.e. $G_n(w)$ is functionally dependent on x_{ni} – will always be "consistent with observed behaviour." This likely extends to discrete choice models but has not been clearly analyzed (Brock and Durlauf, 2001). Nonetheless, group membership has been inferred in applied work such as Walker and Li (2007) and Chen (2012) who applied latent class models to identify lifestyle groups in discrete choice decisions. Dugundji and Walker (2005) and Sidharthan et al. (2011) used goodness-of-fit measures such as log-likelihood ratio tests and non-nested tests to test various hypothesized network structures. Additionally, Sener et al. (2010) used a copula approach to allow for varying strengths of correlations between different intra-household members. More research is needed on goodness-of-fit measures and new data is needed with qualitative social interactions data and explicit networks and group memberships.

7.2. Qualtitative approaches

Qualitative study can provide guidance for modeling efforts but has seen limited use in transportation. Clifton and Handy (2003) suggest the use of interviews and focus groups in travel behavior research. Additionally, Akerlof and Kranton (2002, 2010) recommend the use of ethnographies for economic models involving group definitions and expectations of group behavior. Abdelal et al. (2009) classifies the most common techniques for measuring identity in social science studies as: surveys and interviews, content analysis, discourse analysis and ethnography, cognitive mapping, and experiments. Specific examples in transportation include:

- Axsen and Kurani (2012) identify contagion, conformity, and dissemination as possible sources of influence in electric vehicle purchasing decisions.
- Lovejoy and Handy (2011) study how social context affects carpooling among immigrants while Mote and Whitestone (2011) study informal commuting (slugging).
- Bartle et al. (2013) study social influence in cycling commuting through the interaction of cyclists on an online social networking site, questionnaires, and semi-structured interviews.

Qualitative methods can be used to increase the credibility of model assumptions on appropriate group memberships, group salience, and expectations of others' behavior. For example, Sherwin et al. (2014) use semi-structured interviews and thematic analysis to analyze cycling behavior in the UK. Their research found that individuals experienced direct social influence from family, friends, co-workers, and government programs. Additionally, individuals also experienced indirect social influence from seeing strangers cycle, varying cycling culture between towns, and gender norms. From this qualitative work, a modeler would have a clearer idea of the relevant influence mechanisms, influence sources, and social network structure for model development. Then, the modeler could use their quantitative results to determine the strength and significance of the social influence.

7.3. Survey design and experiments

It is still rare for travel surveys to cover issues related to social context. Group memberships are not measured in travel surveys

but may be pertinent in the implementation of social influence studies[11]. Models with sparse networks require information on individuals' social contacts in order to create valid weighting matrices. Axhausen (2008) suggests name generators for obtaining lists of contacts, including family members, friends, co-workers, and others. He cautions that name generator questions can increase respondent burden and may suffer from low response rates.

Sampling techniques for social network research in transportation falls into three broad groups:

- *Egocentric*. Egocentric sampling consists of obtaining a random sample of individuals ("egos") then obtaining information from the egos on their direct contacts ("alters"). This has been the primary data collection technique in transportation (Carrasco and Miller, 2006; Carrasco et al., 2008; Carrasco and Cid-Aguayo, 2012; Frei and Axhausen, 2007; Larsen et al., 2008; van den Berg et al., 2008; Scott et al., 2012).
- *Snowball Sampling*. Snowball sampling builds on egocentric sampling by proceeding to collect data directly from the alters of the initial random sample of egos. This allows for an analysis of indirect contacts and the structure of networks, as done by Kowald and Axhausen's (2012, 2014) analysis of personal leisure networks.
- *Census*. In a census, the connections of all individual in a network are observed. This is a rather difficult task for large populations and when population boundaries are difficult to determine. This technique has strengths in small groups and institutions or when the collection of social contacts is easily logged (e.g. social networking sites, smartphone applications).

Even with explicit questions about networks and influence sources, it is often difficult to pinpoint social influence effects. To control for non-social factors, experiments are an avenue to determine whether social influences are prevalent in travel behavior (Sunitiyoso et al., 2011). Gaker et al. (2010) explores hypothesize that "social influence in the form of an information cascade will affect whether a person buys a conventional car, buys a hybrid car, or forgoes having a car" (p. 52). Result from their information cascade experiment revealed that subjects who were shown the prior choices of other respondents were more likely to pick the most chosen option.

7.4. Random network models

Large-scale social network data is difficult to find due to the need for extensive collection efforts plus privacy and ethics concerns. In order to create realistic imitations of real-world social networks, modelers may use random network models in simulations and agent-based models. In Arentze et al. (2012), the authors used common concepts from social network analysis – homophily, propinquity, and transitivity – to create a static, stochastic, actor-based model of network formation. Dugundji and Gulyás (2003) looked at Erdős–Rényi (Erdős and Rényi, 1960) and small-world network models to analyze the equilibrium behavior of utility maximizing agents. Observing patterns of emergent behavior can guide future research study design to optimize resource allocations for new social influence studies. If the structural properties of the network are only needed, modelers may use random graph models, such as Erdős–Rényi, Barabási–Albert (Barabási and Albert, 1999), and Watts–Strogatz (Watts and Strogatz, 1998) models, to generate expected graph structures. Otherwise, if information on user attributes exists, modelers may use game-theoretic network models (Jackson, 2010) and exponential-family random graph models (ERGMs) (Lusher et al., 2012).

[11] Woittiez and Kapteyn (1998) provide an example from labor economics.

8. Summary and future research

In this paper, a generalized framework to behaviorally describe choice models of social influence was presented. The framework emphasizes the similarities in different forms of social influence models previously presented in the literature and brings focus to the role of social networks in these models. This paper focuses on the behavioral modeling and data concerns with four of the framework's components: social influence mechanism, social networks, and endogenous and exogenous influence sources. An understanding of the motivations for social influence has a critical role in determining the social network and influence sources to use in modeling different choice behavior. The interdependence of these aspects affects the behavioral explanation of choice decisions which will have impacts on the effectiveness of different policy prescriptions. Because of the complexity of social influence and the various and conflicting motivations for social influence, it is critically important to understand the behavioral process rather than solely comparing competing model specifications for statistical significance alone. As Kadushin (2012) explains, identifying influence is difficult due to:

- "the practical problems of finding the influencers",
- "the theoretical problems of modeling the source and nature of the influence," and
- "distinguishing between the effect of media and the social environment and specific individuals who might inform or persuade (or both)" (p. 140).

These differences in social influence types, motivations, tactics, and sources have important implications in applying these models for policy analysis since short-run and long-run behaviors can vary.

Issues with identification make the design of social influence studies vital in correctly determining social impacts. Prell (2012) summarizes the process of conducting a social network analysis study as follows:

1. *"Read up on the literature"* Using prior knowledge in the field of study will be valuable in directing the research design. This can guide researchers to the appropriate survey designs and data sources, likely social influence motivations, or social network structures.
2. *"Develop a theoretical framework"* This paper provides a general framework for the choice modeling of social influence. The components of the framework – social networks, social influence mechanism, and decision rules – allow a variety of behavioral and sociological theories to be incorporated such as social influence network theory (Friedkin and Johnsen, 2011), diffusion of innovations (Prell, 2012), social comparison (Abou-Zeid and Ben-Akiva, 2011), information cascades (Gaker et al., 2010), and the social identity approach.
3. *"Develop research questions or hypotheses"* Linking social influence and travel is still a relatively young field and a number of applied and theoretical questions are still unanswered. In applied work, this is a rather important step because of the difficulty in identifying social influence in cross-sectional or even panel data because of the possibility of correlated effects. Thus, researchers attempting to make inferences must have a clear idea of what they are testing for before they begin modeling.
4. *"Determine your population of interest, sample, and network boundary"* Aside from trivially small or isolated populations, determining the appropriate sample for a social influence study is open-ended. Boundary determinations are tricky and study designs may depend on modeler assumptions or respondent-reported boundaries (or both).

5. *"Gather data"* As shown in Section 7, gathering network and influence sources data can be driven by choice-data, qualitative, survey, experimental, and graph model methods. The tradeoffs between the techniques need to be considered in a study's context.
6. *"Analysis and interpretation of results."* The modeler uses the data, prior literature, and theoretical framework to create an appropriate model to answer their research question.

The flexibility of the framework presented can be used as a taxonomy for describing social influence models of discrete choice as well as a springboard for further research and application. In particularly, new focus can be applied to:

- New decision rules such as regret minimization (Chorus et al., 2008, Chorus, 2010, Zeelenberg and Pieters, 2007), prospect theory, elimination by aspects (Hess et al., 2012), and decision trees.
- Heterogeneity in the social influence mechanism depending on classes of individuals.
- Deriving and analyzing dynamical and equilibrium behavior beyond reflexive large cliques and mean-effect conformity due to the greater variety of social influence processes, network configurations, and decision rules possible.
- Mixing social network types and structures when using multiple social influence mechanisms.
- Understanding and incorporating cognitive and spatial limitations on network formation.
- Exploratory work to find new influence sources that affect social influence besides the choices of others such as attitudes, perceptions, past experiences, ideal types, and the salience of social identities.
- Panel data collection of behavior and social networks over time will allow researchers to more accurately identify the existence of social influence effects by controlling for correlations between social networks and influence sources.
- Developing and applying dynamic models of network formation and discrete choice (Gulyás and Dugundji, 2006; Snijders et al., 2010).
- Applying random network models for policy analysis to deal with issues of privacy and ethics in social network data collection.
- Assuming more complex payoff forms beyond the linear-in-parameter formulation such as multiplicative combinations of factors (e.g. cross effects).
- Incorporating network statistics (e.g. centrality, closeness, diameter) into the modeling process as explanatory variables (Dugundji et al., 2011a,b) or to trigger changes in social network mechanisms and influence sources.

Social influence in travel behavior is a thriving research area in the travel behavior community, but careful consideration of the limitations of current models and data are warranted. These concerns may limit the application of these methods by institutions and policy makers, so the field must mature in the strength and accuracy of its claims with appropriate data and models with predictive capabilities.

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