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Decision makers and socializers, social networks and the role of individuals as participants

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Abstract Models explaining and predicting human travel behavior have gone through many changes in the past few decades. As researchers attempt to explain more and predict with more accuracy, the inclusion of social interactions in modeling and simulation is being recognized as a necessity. Among these efforts, researchers have focused on issues such as the composition of social networks, and the constraints and influences that others have on spatial decisions. An important aspect that has been understudied however is the variability or heterogeneity of individuals both as social network members and as participants in these social networks. Understanding the role individuals play in decision-making in different social networks can further define our models to include more accurate representations of human behavior. This research explores the differences between social network composition, and the decision roles members play within different social networks specifically when deciding where to participate in activities. A survey was conducted in Santa Barbara, California on social network involvement, network attributes and decision-making roles within each network. Two separate latent class cluster analysis models were developed to classify social network involvement and roles. Results show that there are clearly different types of social involvement and roles within networks. Further data collection and analysis will be used to better understand how these decision-making roles manifest themselves in activity decision-making.

Keywords Travel behavior · Social networks · Decision making · Destination choice

Introduction

Current practices within travel demand rely on the use of activity based modeling methods. Foundational to this modeling framework is the concept of travel being a derived demand

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from the necessity or desire to participate in activities (but also travel as a desirable activity per se). This paradigm has reshaped the approach that is taken to modeling individuals in a transportation setting. It is being recognized however, that the assumption and simplistic representation of activities as being economically and psychologically driven is not all that is needed. Activities many times are social in nature, and should be modeled as such. Even when activities are not social in nature, it is possible that they are influenced by other social activities that could constrain the time and space dimensions of an activity (Páez and Scott 2007). Several attributes of activities are considered in modeling behavior as well as important factors that influence the choice process.

Although the literature is just recently gaining momentum within travel behavior, the acknowledgement of the influence of others on time use and travel behavior has long been realized. For instance, Salomon (1985) made the claim that the desire for a sense of belongingness drives people to want to participate in activities. This in turn drives the need for travel, as already discussed as a premise of the activity based approach. In addition to this, the time geography concept of “coupling constraints” has been empirically examined by researching the influence of social contacts on an individual’s travel (Páez and Scott 2007). The broader concept of social networks has also been explored by several others (Axhausen 2005, 2007; Arentze and Timmermans 2008; Carrasco and Miller 2006; Habib and Carrasco 2011). As stated by Páez and Scott (2007), “the need for social contact, and the effect of social influence on travel behavior, is one such aspect of decision-making that deserves attention.” Prior to these explorations arising in the mid to late 2000’s, other considerations in social influences had debuted in the travel behavior research community (Kitamura 1998). Details such as with whom activities and travel were conducted (Harvey and Taylor 2000; Habib et al. 2008), or for whom the activity was conducted (Goulias and Kim 2004) have made their way into surveys as interesting and thought provoking data types, leading to pioneering analyses. Although the social aspects of these examples are more broadly cast, research focused on understanding within household interaction and the implications of these interactions on time use and travel behavior has received most of the attention regarding social influences (Gliebe and Koppleman 2002; Golob and McNally 1997; Yoon and Goulias 2010), and can be more easily analyzed with a household level data collection exercise.

In addition to the research discussion based on social influences, several researchers have focused more specifically on the composition of social networks from a traditional social network definition. The original use of the metaphor of a network to describe a person’s social relationships came from a group of sociologists in Germany (Scott 1988). Social networks are made up of nodes (people), which are connected by links. The analysis of these social networks, using techniques such as graph theory, gives researchers a computational representation of the relationships and possibly the connectivity between people (closeness, interconnectedness, etc.). Carrasco and Miller (2009) break down several characteristics into various elements. First, the composition of a social network identifies the number of similar relationships to the individual (e.g., family, friends, coworkers, schoolmates, fellow church goers) and the level of closeness of each of these types of relationships. Second, they identify several key characteristics defining the network structure (the size, instances of isolates or people only connected to the individual, density, network subgroups and potential of activity propagation from different types of relationships or people). These elements provide a theoretical basis for the development of survey questions used in this research to understand social networks and their contribution to decision making.

In order to develop the most accurate models of decision making and behavior, it is therefore important to keep in mind that the manner in which social networks influence

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behavior, and explore ways in which they can be introduced into models. Much of the current practices in travel demand modeling rely on modeling the choice process. It is recognized through several theories that social influences impact behavior, and therefore implicitly the decision making process. For instance the Theory of Planned Behavior (Ajzen 1991) includes the influence of social norms. In addition, many theories focus on the attainment of social capital, which includes by nature social interactions and influenced decision processes (Bourdieu 1984, 1998). Within travel behavior, researchers have focused on several aspects of social activities. For instance: telecommuting (Páez and Scott 2007), the propensity to conduct social activities (Carrasco and Miller 2006) and activity duration (Habib and Carrasco 2011). In addition, research has extended into examining who activities are conducted with and their social nature (Sener and Bhat 2007), as well as both with whom and for whom an activity is conducted (Goulias and Kim 2004; Goulias and Henson 2006). We envision developing choice models that explicitly incorporate the power in decision making of individuals in social networks. These models will most likely be task and time allocation models with the important addition of representing power in a system that has explicit unequal power among agent-roles. Before developing the functional forms and deriving the mathematical apparatus to estimate models of this type we need to understand the roles played by individuals in different decision contexts. One example of this "negotiation" and task allocation within a household is the generation and allocation of escort responsibilities in a household (e.g., taking children to school or a household member needing medical attention to the doctor) and its associated household car type allocation (Bhat et al. 2012). In activity location choice or destination choice we do not have models that explicitly assign decision roles among the persons participating in the activity at the destination. To develop this type of choice models in activity-based model systems it is very important to identify the power structure in decision making when groups of individuals participate in activities. These concepts have yet to be woven sufficiently into the framework of discrete choice models, which are perhaps the most widely accepted models for decision making. In order to do this, we must first examine the roles that different social networks play in decision processes, and determine how best to represent heterogeneity among social interactions.

Data description

The data used in this study is a portion of a survey conducted in Santa Barbara, California. The data collection consisted of a mail recruit letter, with a web based response. The survey included questions about social network involvement, size, strength and frequency of contact of the social network, and the role the respondent plays in decision making for activities conducted with that specific network type. The survey also included a section of household and individual level socioeconomic and demographic questions, as well as several additional sections regarding general decision making linked to destination choices. The resulting sample statistics are provided in Table 1 from a total of 574 respondents.

Each respondent was asked to select from a list of seven different social network types the groups in which they interacted with in a typical week. The list of social network types was developed using research conducted by Carrasco and Miller (2006) and Goulias and Kim (2004). This list included immediate family, extended family, friends, coworkers, students (peers), students (as a mentor) and organization members (religious, sport, club, etc.). Following the selection of networks, four questions were asked for each of the social

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Table 1 Sample descriptive statistics

Variable	Description	
Gender	Female	59 %
	Male	41 %
Employment	Employed full time	44 %
	Employed part time	14 %
	Student full time	6 %
	Student part time	1 %
	Self employed	7 %
	Home duties	4 %
	Unemployed	4 %
	Looking for work	1 %
	Retired	17 %
	Disabled	2 %
Marital status	Single, never married	23 %
	Married/domestic partner	61 %
	Other	16 %
Relation to household	Live alone	13 %
	Live with immediate family	72 %
	Live with extended family	3 %
	Live with friends	5 %
	Live with acquaintances	2 %
	Live with significant other	3 %
	Other	2 %
Age	Mean	49 years
Household income	Median	$60,000–$69,999
Number of children	Mean	0.47
Number of household members	Mean	2.6

networks selected regarding size, strength, frequency of contact and decision-making role. Figure 1 provides the questions from the survey.

Methods

In order to understand the way in which people are involved in different social networks, and the role that they play in the decisions involved in these groups, latent class cluster analysis was used. Latent clusters or groups developed from the statistical procedure were used to first classify aspects of social networks and their composition, and second understand social interaction roles.

Latent Class Cluster Analysis (LCCA) is a modeling technique within the latent class models in which probabilistic methods are employed to cluster or group objects (or in our case individuals) into classes. Although the basic form of the LC cluster model is one with

Fig. 1 Page one and two of social networks survey questions

continuous indicators, extensions have been developed to accommodate mixed indicator types (including nominal and ordinal) and covariates to be simultaneously modeled. The equation used for LCCA with mixed indicator types is provided in Eq. 1.

$$f(y_i|\theta) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} f_k(y_{ij}|\theta_{jk}) \qquad (1)$$

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where

y_i is the person's response ($i = 1,\ldots,N$) to the measured variables and $y_i|\theta$ is the distribution of y given the model parameter θ; N is the number of respondents; K is the number of clusters ($k = 1,\ldots,K$); π_k is the prior probability of belonging to a latent class or cluster *k;* J is the total number of indicators

And y_{ij} is each element of y_i used to individually specify each univariate distribution. These are the scores for each respondent's answers of the questions in Fig. 1.

In addition to this specification, covariates can be used to predict class membership. When specifying these covariates, it is important to separate them as exogenous variables used only to predict membership, and not as endogenous variables used to inform the development of clusters. Equation 2 provides the formulation for the inclusion of these covariates.

$$f(y_i|z_i,\theta) = \sum_{k=1}^{K} \pi_{k|z_i} \prod_{j=1}^{J} f_k(y_{ij}|z_i,\theta_{jk}) \qquad (2)$$

where

z_i is the vector of the values of the covariates for individual i. In this model specification, the covariates are specified as having direct effects, avoiding the influence of the covariates effect on the class membership only going through the latent variable.

The analysis was conducted using Latent Gold 4.5. To estimate the parameters, Maximum Likelihood (ML) and Posterior Mode (PM) methods are traditionally used. PM methods account for the use of several priors (Dirichlet and Gamma) employed to avoid boundary solutions or non-existence of Maximum Likelihood estimates (Vermunt and Magidson 2005). In order to converge to a solution, Latent Gold estimation procedures include a two-step use of algorithms, first using Expectation Maximization (EM) and turning to Newton–Raphson (NR) once a solution is near the Likelihood maximum. Models of different cluster structures were estimated iteratively and compared. Model parsimony, fit statistics and cluster structure were all used to determine the appropriate number of clusters best describing the data and latent phenomenon.

Conceptual framework

In order to understand both the composition of different social network types and the different roles that people have in those networks, a two stage cluster model was developed. The first step consisted of developing a classification of instances of respondents' social network involvements dependent on network composition. In the second step, these classifications of social network involvement types were used with decision making responses to understand differences in socializer types, or the role people play in different instances of social network interactions.

Social network composition

The analysis of social network composition included three measured attributes of the social network. The stated size of the social network, perceived strength of the relationships the respondent had with individuals in the specific network, and frequency of interaction (see Fig. 1) with the social network were used to create clusters of social network composition types. Covariates of the type of social network were included to further drive the

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estimation of clusters and classifications. The conceptual model for this stage of estimation is labeled as "Model 1" in Fig. 2. Development of this cluster model provided one classification for a number of social network attributes, which describe a specific instance of social interaction type. Each social group for each individual was assigned a cluster class as a result of this first stage.

Social engagement types

Following model one, the cluster memberships were used to provide further insight into social aspects and roles. Model one classifications were used in combination with responses about the decision making role (who decides the location where activities take place) to develop socializer type clusters (represented as "Model 2" in Fig. 2). These socializer clusters were again classes of specific instances of social network interaction for each respondent. Development of these clusters was used to investigate the possibility that differences in roles exist among different social group types.

Analysis

In accordance with the conceptual framework provided in the previous section, two latent class cluster models were developed. The sample consisted of 1,764 different instances of social network involvement from 574 respondents. Descriptions of the social network data is provided in Fig. 3. Respondents recorded participation on average with three different types of social networks, with 98 % of respondents falling between one and five different social network types.

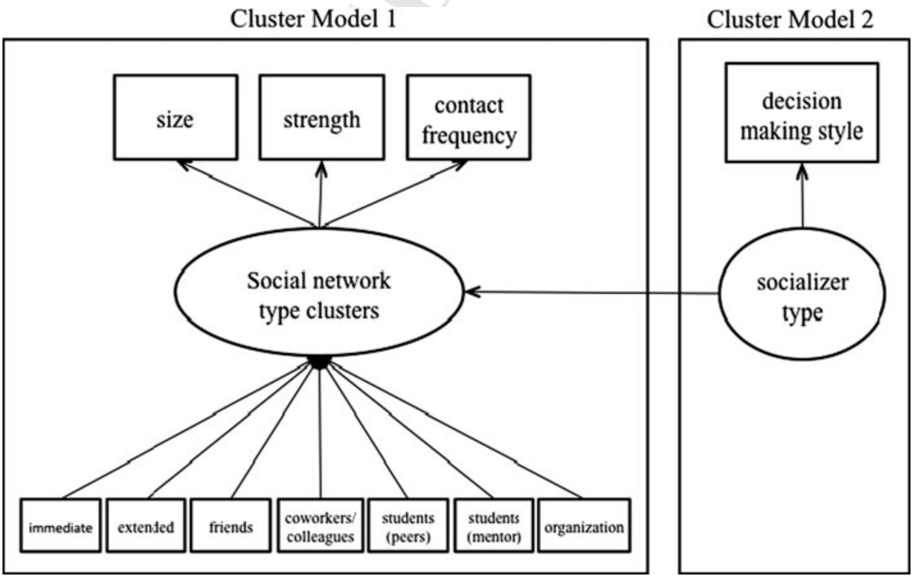

Fig. 2 Conceptual model

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Cluster model 1 (social network types)

An iterative procedure was used to develop a series of cluster models based on social network aspects provided both as exogenous and endogenous variables. Social network size, strength and frequency of interaction were used to inform the development of the latent clusters, while the types of network were used as binary covariates. For estimation purposes, one binary indicator (in this case organizations) must be left out of the model specification. Each instance of social network involvement was treated as an individual object to be classified in the cluster model, therefore classifying instances of participation. It is therefore possible for most individuals to have memberships in different clusters,

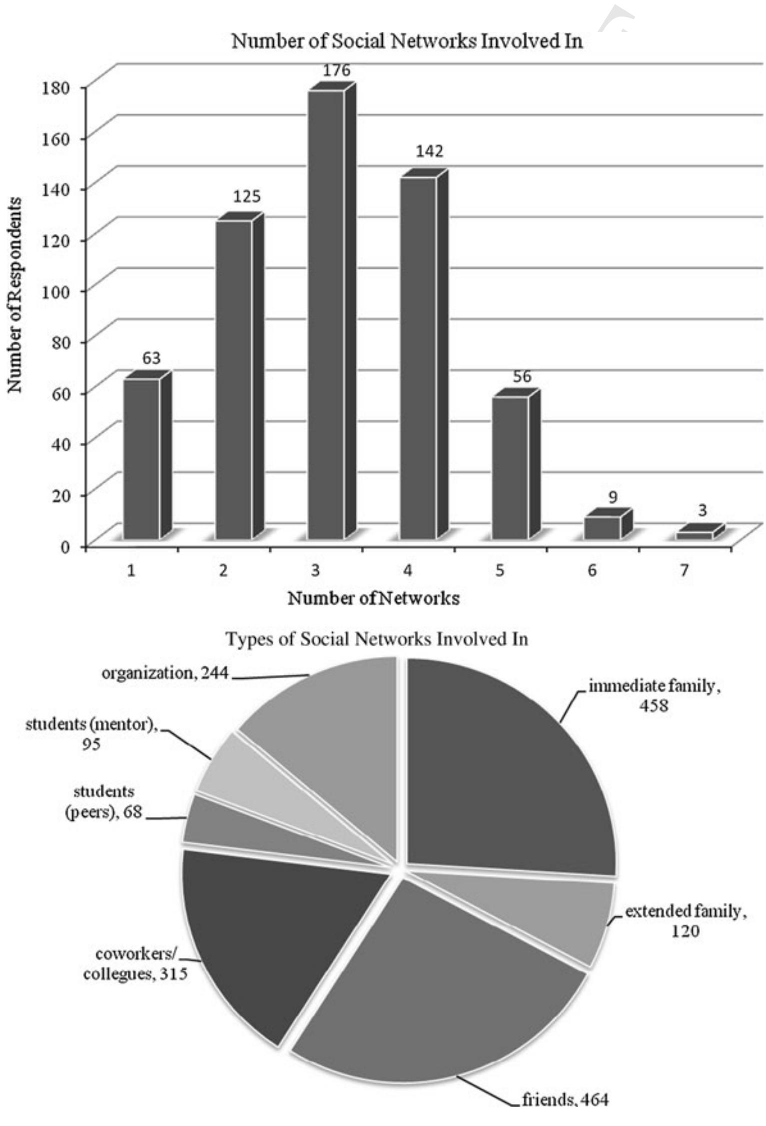

Fig. 3 Sample social network statistics ($N = 574$, Mean: 3.07, Standard deviation: 1.231)

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dependent on the social network involvement. The resulting model, a 5 cluster model was determined to be the best model representing the data based on fit statistics (provided in Table 2), model parsimony and cluster structure. The resulting profile of this five-cluster model is provided in Table 2, and the probability means are reported in Table 3. The five clusters developed are interpreted as shown in Fig. 4 that shows the relative value of three criteria variables (network size, strength of relationships, and contact frequency) within each cluster.

The covariates included in the model estimation provide insight into the types of social networks that are present in each cluster. Cluster one for example consists mainly of immediate and extended family, as well as friends. The probability means indicate that instances of both extended family and friends have high probability of belonging to cluster one. This finding indicates that there is similarity among these three types of social networks in the composition of size, strength and frequency, especially in the case of extended family and friends. Cluster two is largely represented by immediate family social network instances. This cluster also includes a portion of the extended family and friend social network instances, but is mostly dominated by immediate family. This result is to be expected, as it shows that networks instances of immediate families have qualities of their composition (relationship strength, size and level of interaction) that are not as common to other network types. Clusters three, four and five are primarily composed of non-family or friend based social network types. Commonality is again noticed, this time between coworker social network types and students (either as mentors or peers) within both cluster three and cluster five. To further the explanation of cluster classification and social network type, a visualization of a cross-tabulation of cluster class and network type is provided in Fig. 5. Notably, this graph illustrates the strong domination of organization social networks in cluster four. Cluster four primarily consists of large social networks, with strength of relationships in the middle to somewhat strong region on the spectrum. Cluster 3 appears to be dominated by professional colleagues and coworkers/students.

Cluster model 2 (decision roles)

Following the development of a cluster model based on social network types and attributes, the decision roles of individuals with respect to the social network involved in were cross-tabulated. The results of this cross-tabulation were used to examine the commonalities and distributions of decision making roles when deciding where activities take place with others from a social network or role across social network types. Decision types were categorized into five groups as a result of responses from the survey. The first three decision types correspond to each of the response options of the survey, which have been shortened for ease of reference. Responses of “I generally have a large say in the decision making process” were termed *leading decision maker*, “I partake in decision making, but not more than most others” were termed *equal collaborator*, and “I usually just go along with decisions made by others” were termed *decision follower*. Additionally, the survey form allowed for an “other” response, allowing respondents to explain their selection of “other.” Many of these explanations indicated the fixed nature of activities with these social groups. For instance explanations like “usually fixed meeting places” or “The location of volunteer activities I participate in is already known” were given. Individuals selecting the “other” option for their role were categorized as *other decision-making role*. Lastly, due to the fact that respondents were allowed to select multiple response variables describing their decision making role in the network, a fifth categorization was created. The explanation respondents gave for selecting multiple roles consisted of statements such

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Table 2 Model One Profile

			Cluster1	*Cluster2*	*Cluster3*	*Cluster4*	*Cluster5*
		Cluster Size	0.3815	0.2209	0.1604	0.1544	0.0827
Indicator	size	1-5 persons	0.5074	0.9441	0.4452	0.0748	0.2698
		6-10 persons	0.2907	0.0533	0.2976	0.1376	0.2733
		11-20 persons	0.1421	0.0026	0.1697	0.2160	0.2362
		21-50 persons	0.0474	0.0001	0.0661	0.2314	0.1393
		51-100 persons	0.0083	0.0000	0.0135	0.1297	0.0430
		Over 100 persons	0.0042	0.0000	0.0079	0.2104	0.0384
		Mean	1.7709	1.0586	1.9287	3.8350	2.5274
	strength	1	0.0001	0.0000	0.0210	0.0094	0.0030
		2	0.0003	0.0000	0.0346	0.0181	0.0072
		3	0.0022	0.0000	0.0920	0.0568	0.0275
		4	0.0056	0.0000	0.0941	0.0684	0.0407
		5	0.0334	0.0001	0.2230	0.1909	0.1392
		6	0.0720	0.0009	0.1917	0.1934	0.1727
		7	0.1540	0.0081	0.1635	0.1943	0.2126
		8	0.3088	0.0652	0.1308	0.1831	0.2456
		9	0.2050	0.1746	0.0346	0.0571	0.0939
		10	0.2185	0.7511	0.0147	0.0286	0.0576
		Mean	8.2077	9.6665	5.6571	6.2290	6.8689
	contact	Everyday	0.0255	0.7264	0.0014	0.0178	0.4359
		A few times a week	0.3873	0.2689	0.0617	0.3213	0.5317
		Once a week	0.2744	0.0046	0.1254	0.2702	0.0303
		A few times a month	0.2316	0.0001	0.3039	0.2707	0.0021
		Once a month	0.0524	0.0000	0.1974	0.0727	0.0000
		Less than once a month	0.0287	0.0000	0.3102	0.0473	0.0000
		Mean	2.9843	1.2785	4.5649	3.2010	1.5986
Covariates	immediate	0	0.8462	0.1011	0.9889	1.0000	0.9919
		1	0.1538	0.8989	0.0111	0.0000	0.0081
		Mean	0.1538	0.8989	0.0111	0.0000	0.0081
	extended	0	0.8605	0.9596	0.9661	0.9974	0.9998
		1	0.1395	0.0404	0.0339	0.0026	0.0002
		Mean	0.1395	0.0404	0.0339	0.0026	0.0002
	friends	0	0.3807	0.9672	0.9138	0.9961	0.9388
		1	0.6193	0.0328	0.0862	0.0039	0.0612
		Mean	0.6193	0.0328	0.0862	0.0039	0.0612
	coworkers	0	0.9335	0.9894	0.3590	0.9934	0.4316
		1	0.0665	0.0106	0.6410	0.0066	0.5684
		Mean	0.0665	0.0106	0.6410	0.0066	0.5684
	peers	0	0.9942	0.9999	0.8874	0.9157	0.9367
		1	0.0058	0.0001	0.1126	0.0843	0.0633
		Mean	0.0058	0.0001	0.1126	0.0843	0.0633
	mentors	0	0.9975	1.0000	0.9083	0.9095	0.7072
		1	0.0025	0.0000	0.0917	0.0905	0.2928
		Mean	0.0025	0.0000	0.0917	0.0905	0.2928

BIC = 15529.1694, Classification error = 0.1091

as "it depends on the decision" or "there are three of us, and we all at times feel what one wants to do is more important than others." These multiple response instances were collapsed into one variable, and were categorized as *mixed decision role*.

Results of the cross tabulation are provided in Fig. 6. Of note, decision followers primarily manifest within colleagues/coworker social networks, and organization instances. The "equal decision making" role is represented in each of the network types,

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Table 3 Model 1 probability means

			Cluster1	*Cluster2*	*Cluster3*	*Cluster4*	*Cluster5*
		Overall	0.3815	0.2209	0.1604	0.1544	0.0827
Indicators	size	1-5 persons	0.3669	0.4112	0.1497	0.0205	0.0518
		6-10 persons	0.5623	0.0543	0.1991	0.0956	0.0888
		11-20 persons	0.4166	0.0045	0.1821	0.2749	0.1220
		21-50 persons	0.1980	0.0000	0.1698	0.4685	0.1638
		51-100 persons	0.0793	0.0000	0.1126	0.6188	0.1893
		Over 100 persons	0.0359	0.0000	0.0284	0.8564	0.0793
	strength	1	0.0206	0.0000	0.4998	0.2866	0.1929
		2	0.0063	0.0000	0.6069	0.2925	0.0942
		3	0.0278	0.0000	0.5250	0.3183	0.1289
		4	0.0336	0.0000	0.4233	0.4588	0.0843
		5	0.1590	0.0002	0.4144	0.3012	0.1253
		6	0.2487	0.0001	0.3647	0.2772	0.1094
		7	0.4720	0.0120	0.1813	0.2104	0.1242
		8	0.5681	0.0703	0.1013	0.1558	0.1044
		9	0.5625	0.2887	0.0262	0.0474	0.0751
		10	0.3208	0.6324	0.0084	0.0223	0.0161
	contact	Everyday	0.0438	0.7715	0.0012	0.0105	0.1730
		A few times a week	0.4877	0.1855	0.0343	0.1513	0.1412
		Once a week	0.5547	0.0105	0.1180	0.3022	0.0146
		A few times a month	0.5496	0.0003	0.2577	0.1914	0.0010
		Once a month	0.2980	0.0000	0.5350	0.1669	0.0000
		Less than once a month	0.1370	0.0000	0.7298	0.1333	0.0000
Covariates	Immediate	0	0.4361	0.0302	0.2143	0.2086	0.1108
		1	0.2259	0.7646	0.0069	0.0000	0.0026
	Extended	0	0.3523	0.2274	0.1663	0.1653	0.0888
		1	0.7826	0.1312	0.0799	0.0059	0.0003
	friends	0	0.1971	0.2899	0.1989	0.2087	0.1054
		1	0.8984	0.0275	0.0526	0.0023	0.0192
	coworkers	0	0.4336	0.2660	0.0701	0.1868	0.0435
		1	0.1421	0.0131	0.5758	0.0057	0.2633
	peers	0	0.3945	0.2297	0.1481	0.1471	0.0806
		1	0.0572	0.0004	0.4688	0.3379	0.1358
	mentors	0	0.4023	0.2334	0.1540	0.1485	0.0618
		1	0.0174	0.0002	0.2732	0.2595	0.4497

although is small in the cases of interaction with students as a mentor. This social network type is predominately comprised of leading decision makers" who have the most influence in the decisions, which is an intuitive role of someone in a mentoring relationship.

In addition to the cross-tabulation, a second latent class cluster analysis was conducted to examine the stated roles respondents have in decision-making processes among the clusters developed by network attributes. The membership classifications of the latent class cluster model previously discussed were used as an indicator in the estimation of the second model. In addition to classification results, the stated decision-making role variable was used in the development of clusters. An iterative procedure was again used in specifying the model structure. The fit statistics (provided in Table 4), cluster structure and classification error were used to guide the final acceptance of the four-cluster model. Results of this second model are provided in Table 4 (profile) and Table 5 (probability means). The results of this cluster analysis provide some interesting insights on decision-making styles within different social contexts. Clusters can be described as:

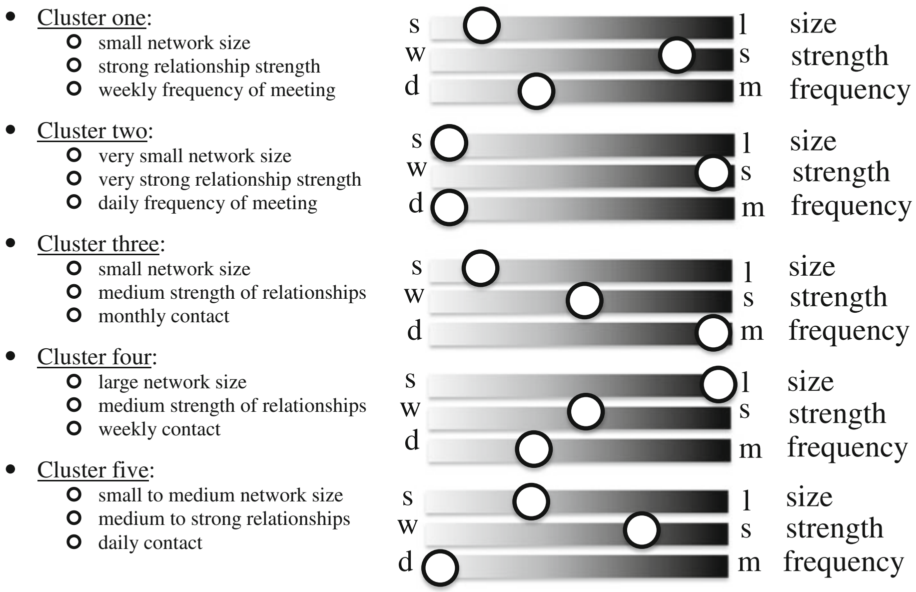

Fig. 4 Cluster results of network attributes (note that for size *s* small, *l* large; for strength *w* weak, *s* strong; and for frequency *d* daily, *m* monthly)

Cluster one

This cluster is largely comprised of family and friends with small size, strong relationships and frequent interaction. The predominant decision role in this cluster is either leading decision maker having large influence, or equal collaborators in the decision.

Cluster two

This cluster is mainly comprised of non-family or friends social networks, and it is the cluster with the highest probability for organization instances. The decision-making role is mostly decision follower, with some equality of decision making with a collaborator.

Cluster three

This cluster is comprised mostly of the small size, strong relationships, weekly interaction cluster, which is largely based on social networks of friends. The decision making role for this cluster is mostly decision followers or mixed decision strategies.

Cluster four

This cluster is comprised mostly of organization, mentor and coworker social network types that are small, and medium relationship strength and everyday interaction. The decision-making role for this cluster is comprised primarily of leading decision makers, and some instances of equal collaboration.

Interestingly, cluster one and three exhibit many similarities in the composition of social network types, as do clusters two and four. The bifurcation of these cluster groups occurs

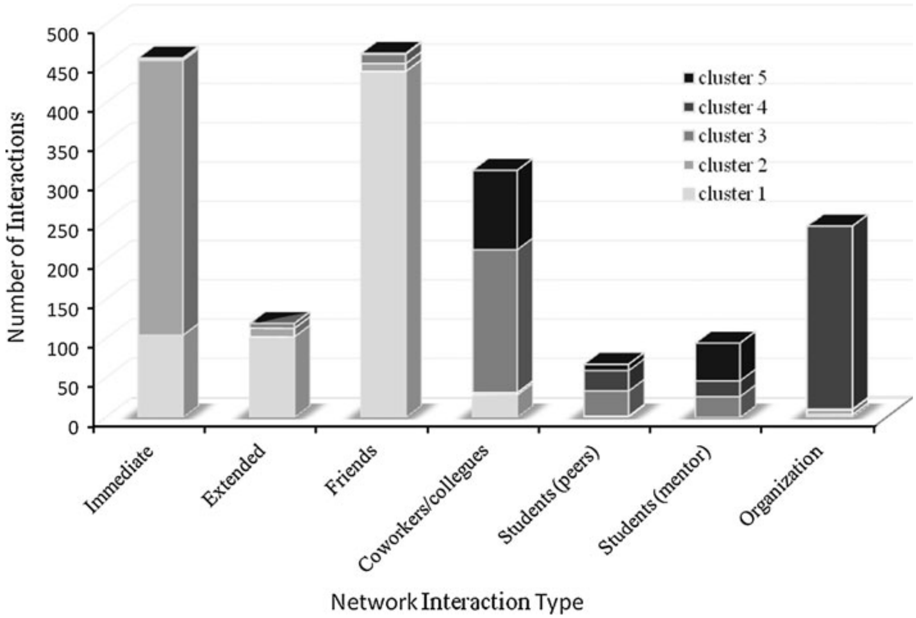

Fig. 5 Social network cluster membership by type

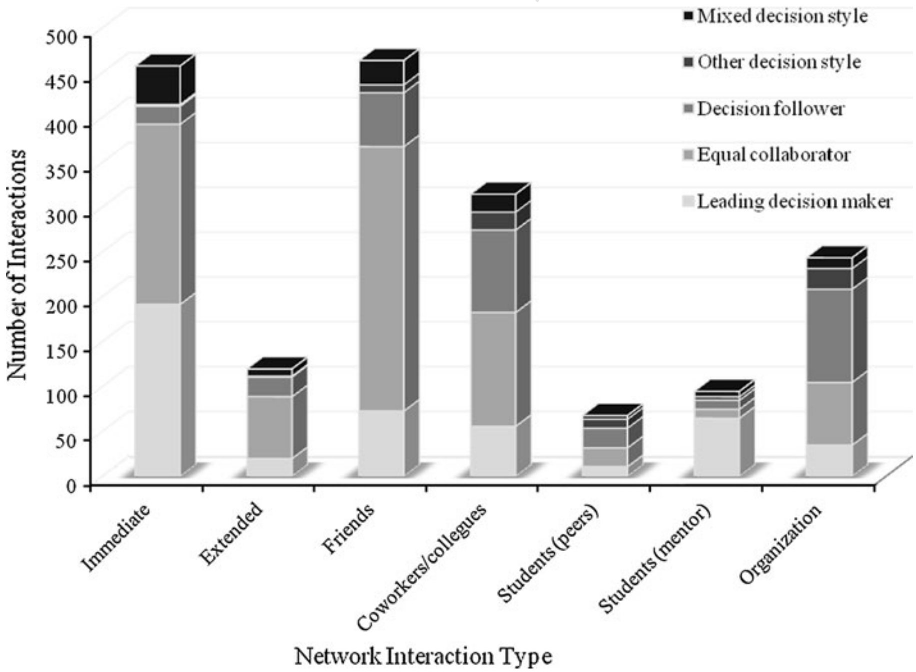

Fig. 6 Decision making types by social network type

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Table 4 Model 2 profile

		Cluster1	Cluster2	Cluster3	Cluster4
	Cluster size	0.5227	0.2395	0.1237	0.1141
Indicators					
Model 1 cluster classification	1	0.5523	0.0000	0.8007	0.0000
	2	0.3663	0.0044	0.1850	0.0001
	3	0.0811	0.4045	0.0143	0.0655
	4	0.0002	0.4701	0.0000	0.3982
	5	0.0000	0.1209	0.0000	0.5362
	Mean	1.5293	3.7075	1.2136	4.4704
Decision type	Leading decision maker	0.3537	0.0002	0.0001	0.6250
	Equal collaborator	0.6438	0.2355	0.1123	0.3745
	Decision follower	0.0025	0.5444	0.4474	0.0005
	Other decision style	0.0000	0.0943	0.1336	0.0000
	Mixed decision style	0.0000	0.1256	0.3067	0.0000
	Mean	1.6488	3.1097	3.6345	1.3754

BIC = 9783.132, Classification error = 0.0717

Table 5 Model 2 Probability Means

		Cluster1	Cluster2	Cluster3	Cluster4
	Overall	0.5227	0.2395	0.1237	0.1141
Indicators					
Model 1 cluster classification	1	0.7442	0.0000	0.2558	0.0000
	2	0.8908	0.0032	0.1059	0.0001
	3	0.2838	0.6525	0.0116	0.0521
	4	0.0007	0.7175	0.0000	0.2818
	5	0.0000	0.3152	0.0000	0.6848
Decision type	Leading decision maker	0.7210	0.0002	0.0000	0.2788
	Equal collaborator	0.7494	0.1217	0.0341	0.0948
	Decision follower	0.0058	0.6865	0.3074	0.0003
	Other decision style	0.0000	0.8028	0.1971	0.0000
	Mixed decision style	0.0000	0.3658	0.6342	0.0000

due to the difference in roles of decision-making, with decision followers being clearly represented in clusters two and three. The manifestation of these different social roles within two sets of similar cluster compositions indicates that there are both differences in decision-making roles across different types of social networks, as well as heterogeneity within similar social network types.

Conclusions

It is widely accepted that the involvement in activities in different places is a driver of the need for travel. Often times, these activities have a social component, which influences

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either when or where the activity occurs. Many of these social interactions are difficult to capture in current survey methodologies. Household interactions are the exception to this statement, because many travel behavior surveys are collected at the unit of household level. As intrahousehold interactions become an important component of explaining travel behavior, it is important to realize that similar influences occur outside of the household unit. The ability to more accurately predict not only the spatial, but also the temporal attributes of an activity depends on the inclusion of important information. Although this research focuses primarily on the destination choice process, it is important to note that a further need and research direction is the expansion of this decision making analysis to additional attributes of activities such as temporal (daily activity agenda and scheduling of specific activities) or even the overall social composition of the activity (size, social network type, etc.) and how these influence future activities.

To understand the roles of different social networks in the lives of individuals, we must first understand how they differ from each other. A latent class cluster analysis was conducted to examine differences and similarities among different social network types, with respect to the size, strength of relationships and the frequency of interaction. Results show similarities with these attributes among family (immediate and extended) and friends, as well as organizations, coworkers/colleagues, students (as both peer and mentor). In addition to finding similarities, differences stood out as well. For instance, many of the very strong, small family relationships were preserved in a specific cluster.

In addition to the differences and similarities of network composition and type, the decision-making process among these social networks exhibits similar trends. The decision-making role of an individual can differ vastly across different social engagement types. For instance, a parent has a much different role as a member of a family for which he or she is the head; versus the role he or she plays as a member of a company, or friend. The results of the second cluster analysis revealed different groups of decision-making strategies within similar social network types, as well as similarities in decision making strategies across different social network types. This is particularly important for all facets of activity and travel behavior models that aim at describing the decision process followed by individuals and their groups. The research here shows we can identify decision-making roles (leaders vs. followers) and context (family vs. friends social network). It is also possible these roles change with the type of activity or other circumstances. Knowing all this will increase our ability to predict where people will go to participate in activities and also who should be influenced to motivate a group of people in adapting behaviors that are aligned with policies (e.g., sustainability).

In addition to social influences to behavior adoption, the investigation of social networks can provide insight into the spatial distribution of joint activities. An important next step of this research is to determine the patterns of destination choice with respect to the location of individuals prior to a joint meeting. Future data collection and analysis will involve examining activity diaries of individuals and exploring the convergence of time–space prisms of members of different social network types in destination choices. This will allow for investigation as to whether there is correlation between the proximity (closer, equidistant or further) of destinations to a specific individual and the decision-making role. It is quite possible that destination choices for joint activities have a spatial bias towards a more vocal decision maker due to the cognitive processing of alternatives and mental map representations of space. This however must be explored empirically, and requires unique data for the investigation. An enhanced understanding of the process of decision making in this vein as well as a more general knowledge of the joint decision making process will no doubt enhance current modeling efforts. In addition, increasing our understanding of social behavior will provide a richer theoretical basis for the assumptions implicit in the activity based modeling paradigm.

This research was focused specifically on the social network composition and decision making strategies apparent in different networks. Of equal importance however is an understanding of the individual and his or her membership in different social networks as well as decision-making types. Future work includes conducting a person-based analysis, similar to the one presented in this paper, to determine whether it is feasible to predict or model social engagement types with respect to known socio-demographic indicators and membership in different life cycle stages. In addition, this data will be combined with a second phase of data collection consisting of an activity diary and smartphone based activity log. Decision making processes occurring for specific observed activities will be compared to the social engagement types and roles provided by the individual during the first phase of the data collection.

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