Extended Abstract

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ACCOUNTING FOR MULTI-DIMENSIONAL DEPENDENCIES AMONG DECISION-MAKERS WITHIN A GENERALIZED MODEL FRAMEWORK: AN APPLICATION TO UNDERSTANDING SHARED MOBILITY SERVICE USAGE LEVELS

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1. INTRODUCTION

Activity-travel choices of decision makers are shaped by social exchanges with, and observation of behavior of, other proximally located decision makers. Incorporating these notions of inter-dependencies to explain travel patterns and locational choice behavior has garnered much attention in the recent past. However, most of this extant literature invokes spatial or geographic proximity to characterize the strength of association amongst decision makers (Dugundji and Walker, 2005; Bhat et al., 2016). On the other hand, some studies have underscored the significant influence of peers in a decision maker's social sphere (Brock and Durlauf, 2001; Arentze and Timmermans, 2008), regardless of their geographic separation. For example, decision makers in the same social network may actively interact and share information with one another, discuss the positive and negative aspects of alternatives, and thus influence each other's travel choices and purchasing decisions. Furthermore, recent advances in technology and the accompanying growth in social media platforms such as Facebook and Twitter can only accentuate such social influences, as much of these social interactions occur virtually. Within this broader context of growing social interactions, relatively little modeling research has focused on accommodating such interaction effects on travel behavior. This may be attributable to at least three factors: (1) intractability in extracting social network information from traditional transportation and land-use surveys, (2) complexity in delineating the topology of social networks, and (3) lack of methods to operationalize the strength of relationships in such networks (Axhausen, 2008).

In pursuit of a framework that can accommodate social dependency effects in studying travel behavior, this paper extends the concept of proximity-based dyadic interactions by introducing attitudes, habits and lifestyle preferences as new dimensions and measures for defining social proximity. Our proposal is supported by theories in social psychology (Fishbein, 1980; Ajzen, 1991) that evaluate how "soft" attitude and lifestyle factors shape short-term and long-term behavior. As opposed to physical networks that are based on observable socio-spatial variables, this paper introduces *latent social networks* where proximity is evaluated in attitudinal space, mathematically measured using latent constructs.

The proposed methodology accounts for both inter-dependencies amongst decision makers in spatial-attitudinal space and dynamics of self-selection due to inherent attitudes, preferences, and habits affecting usage patterns of car-sharing and ride-sourcing services (collectively termed shared mobility services). Such services have significantly disrupted the urban transportation landscape and ushered in a new era of technology-driven mobility (Hannon et al., 2016; Dias et al., 2017). The paper uses data from the 2015 Puget Sound Regional Travel Study (PSRC, 2015) to model the monthly usage of ride-sourcing and car-sharing services for adults. Monthly usage is characterized as an ordinal variable with three levels (non-users, occasional users, frequent users). The study considers two latent constructs relevant to urban travel and locational behavior: pro-environment attitude and neo-urban lifestyle propensity. The final sample consists of 2170 decision makers who are predominantly employed, middle-aged, car owners, and live in dense areas. Over 80% of decision makers reported not using car-sharing and ride-sourcing services in the past month, consistent with the notion that these services are relatively new in the urban transportation landscape.

The model results reaffirm the interplay of significant (and positive) diffusion effects arising from similarity in attitudinal space, over and above those attributable to spatial proximity, and provides a statistically better goodness-of-fit than models with no dependency effects or only spatial dependence. Decision makers who identify and associate themselves to pro-environmental attitudes and neo-urban lifestyle preferences tend to align their behavior patterns with peers in their social sphere. The unique formulation in the paper can disentangle inter-dependency effects arising from each proximity measure and help compare the relative strengths of different spatial-attitudinal networks. In a nutshell, this paper makes a fundamental contribution to the social and spatial interactions modeling literature by proposing an econometric framework that embodies a simple, yet powerful, mechanism that can help agencies shape more effective policy strategies to influence people's activity-travel choice behaviors.

2. METHODOLOGY

Figure 1 depicts the behavioral framework adopted in this study. Latent constructs (represented as ovals in the figure) that describe a decision maker's innate attitudes and lifestyle preferences are first characterized using appropriate observed indicators (as discussed in more detail later). Then, the latent constructs are linked to the proclivity of using shared-mobility services through dependency effects that propagate over the spatial-attitudinal space. These dependency effects, incorporated as a unified weight matrix (see the right side of the figure), reinforce or moderate the effects of socio-demographic, locational and travel choice variables that affect the frequency of using shared-mobility services.

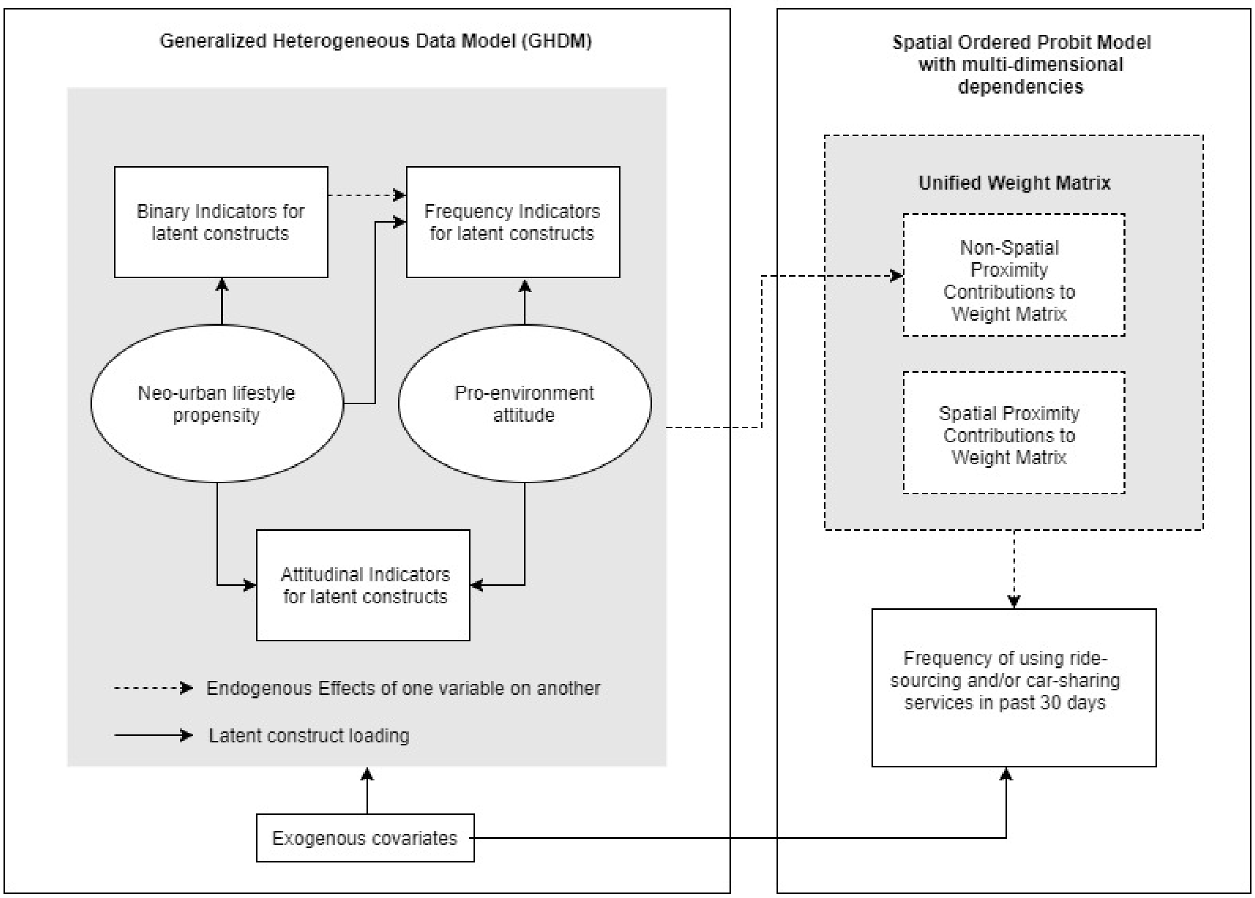

FIGURE 1 Overview of behavioral framework.

The two latent constructs in this study (neo-urban lifestyle propensity and pro-environment attitude) are modeled as functions of exogenous variables and unobserved characteristics, and manifest themselves in the data set as indicator variables that represent observed travel and locational choice behavior, as well as responses to attitudinal questions. Both the latent variables have surfaced in literature as determinants of activity-travel choices, especially in the context of shared-mobility service usage (Efthymiou et al., 2013; Lavieri et al., 2017).

Pro-environmental attitude is reflected in ordinal attitudinal indicators (importance of staying close to transit and importance of residing in walkable neighborhoods) and ordinal frequency indicator variables (frequency of bicycling and walking episodes in past 30 days). The latent factor for neo-urban lifestyle propensity has ordinal attitudinal indicators (importance of residing close to highways and importance of living within 30-minute commute to work, level of interest in participating in autonomous car-sharing system), ordinal frequency indicators (frequency of using technology-based platforms for travel-related information) and a binary variable (smart-phone ownership). Descriptive statistics (Table 1) for the indicator variables show significant heterogeneity in the sample with respect to residential choice location preferences, tech-savviness and interest in futuristic car-share systems.

TABLE 1 Descriptive Statistics of Indicator Variables

Attitudinal (Ordinal) Indicator Variables					
	Response Distribution				
Importance of factor in choosing home location	Very Unimportant 1	Unimportant 2	Neutral 3	Important 4	Very Important 5
Close to major roads/highways	14.8%	16.0%	22.2%	34.6%	12.4%
Being within 30-minute commute to work	11.0%	6.1%	17.7%	20.4%	44.8%
Being close to public transit	15.4%	10.4%	17.8%	25.3%	31.1%
Having a walkable neighborhood and being near local activities	5.3%	6.7%	10.3%	33.2%	44.4%
	Response Distribution				
Level of interest in use of…	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very Interested
Autonomous car-share system for daily travel	55.4%	6.7%	11.9%	14.0%	11.7%

Frequency (Ordinal) Indicator Variables				
	Response Distribution			
Frequency of participating in…	Never	I do, but not in the past 30 days	More than once in past 30 days but at most 1 day/week	Two or more days/week
Bicycling (15 min or more)	62.7%	20.7%	8.4%	8.2%
Walking (15 min or more)	8.3%	6.0%	18.7%	66.9%

Frequency of…	Smartphone ownership and app use for travel info	*Frequency of:*	Technology-based platforms for travel info
Don't own smartphone	30.0%	Never	31.1%
Own smartphone but never use apps for travel info	21.8%	Less than one day per week	33.2%
Own smartphone and use apps less than one day per week for travel info	18.9%	One day per week	12.9%
Own smartphone and use apps one or more days per week for travel info	29.4%	Two or more times per week	22.8%

The modeling framework consists of two linked models: Generalized Heterogeneous Data Model (GHDM) and spatially lagged ordinal response model (SORP) with a unified-weight matrix with spatial and non-spatial (attitudinal) contributions. The GHDM has two submodels – latent structural equation model (SEM) and latent measurement equation model (MEM). In the latent SEM, the latent constructs are represented as linear functions of exogenous variables with stochastic errors. In the latent MEM component, psychometric indicators along with observed travel behavior indicators are posited as functions of latent constructs, exogenous variables, and other endogenous outcomes. The SEM and MEM sub-models are estimated jointly in a simultaneous-equations modelling system using the Maximum Approximate Composite Marginal Likelihood (MACML) approach (Bhat, 2015).

The ordinal variable of interest is modeled using a spatial lag structure with a unified-weight matrix composed of one spatial matrix based on geographic proximity (derived from latitude-longitude coordinates of decision makers' residential locations) and two non-spatial weight matrices formulated using differences in expected latent variable scores. Each constituent weight matrix has a separate coefficient to disentangle the dependency effects associated with each proximity measure (coefficient for spatial matrix is fixed to unity for econometric identification). Unlike previous formulations (Yang and Allenby, 2003), the non-spatial proximity is parsimoniously expressed using the latent variable matrices. By reparametrizing the weight matrix, the formulation allows for the weight coefficients to be negative (and induce counteracting effects) while still ensuring non-negativity of unified-weight matrix elements. The SORP model is estimated using a pair-wise composite marginal likelihood (CML) approach. Since dependency effects dilute rapidly with increasing distance, only pairs of observations within a threshold of eight miles (based on statistical tests in Bhat, 2011) are included in the CML function. The standard errors of the parameters obtained in the SORP model, however, need to be adjusted for sampling error in the expected latent variable scores that are imputed into the unified-weight matrix. The corrections are carried out using the procedure suggested by Murphy and Topel (2002).

3. FINDINGS

This section highlights key results from the SEM component of GHDM and SORP model with multi-dimensional dependency effects. Both models yield estimation results that are behaviorally intuitive and consistent with expectations. Younger and well-educated decision makers are more likely to be pro-environmental and favor a neo-urban lifestyle. Females exhibit a greater sensitivity to environment (Kalof et al., 2002). Lower income groups associate more strongly to pro-environmental attitudes as they are at the receiving end of adverse environmental impacts and use alternative modes more frequently than their wealthier peers. Households with children typically reside in suburbs with larger houses and more vehicles, attributing to lower scores for the two latent constructs. Interestingly, the correlation between the error terms is statistically insignificant.

Table 2 presents the estimation results for SORP models with no dependency effects, only spatial dependency, and both spatial and non-spatial dependencies. In general, frequent users of shared mobility services are younger decision makers, more educated, employed full-time, and reside in higher income households, consistent with findings reported elsewhere (Smith, 2016; Dias et al., 2017).

TABLE 2 SORP Model with Spatial and Non-Spatial Dependencies

Exogenous effects on frequency of using ride-sourcing and/or car-sharing in past 30 days	Aspatial ORP		SORP with Spatial Dependencies Only		SORP with Spatial & Non-Spatial Dependencies		
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	t-stat *
Age (base: 45 or more years)							
18 to 24 years old	0.881	4.49	0.906	10.97	0.598	5.26	5.31
25 to 34 years old	0.661	6.90	0.777	16.11	0.492	5.04	5.11
35 to 44 years old	0.527	5.41	0.573	12.05	0.336	3.77	3.85
Work Status							
Full-time, part-time or self-employed *(base: unemployed)*	0.381	3.95	0.432	9.02	0.227	3.37	3.49
Student *(base: not a student)*	0.253	1.93	0.172	2.94	0.254	12.95	12.24
Income (base: above $100,000)							
Below $25,000	-0.684	-4.57	-0.445	-6.57	-0.741	-19.34	-17.58
$25,000 - $49,999	-0.581	-5.10	-0.513	-8.49	-0.736	-23.31	-20.33
$50,000 - $74,999	-0.366	-3.26	-0.194	-3.30	-0.385	-19.21	-17.25
$75,000 - $99,999	-0.397	-3.51	-0.156	-2.59	-0.318	-17.27	-16.17
Educational attainment (base: less than a bachelor's degree)							
Bachelor's degree	0.386	3.78	0.217	4.10	0.184	4.87	4.96
Graduate degree	0.430	4.00	0.249	4.66	0.182	4.13	4.21
Smart-phone ownership and frequency of usage for travel information in past 30 days (base: don't own a smart-phone)							
Own smart-phone but never use apps	0.881	6.42	0.923	14.25	0.959	22.52	19.65
Own smart-phone and use apps less than once a week	0.800	5.77	0.799	12.22	0.834	22.81	20.08
Own smart-phone and use apps once or more a week	1.080	7.62	1.079	16.49	1.116	23.31	20.26
Own smart-phone and use apps once or more a week x Female	-0.249	-2.28	-0.222	-4.27	-0.263	-14.16	-13.37
Residential Location Density (base: Low Density)							
High Density	0.694	7.64	0.246	5.83	0.497	25.40	22.61
High Density x Presence of at least one kid	-0.416	-2.15	-0.293	-2.95	-0.300	-11.25	-10.82
Vehicle Ownership and Residence Type (base: no vehicles)							
One Vehicle and single-family residence	-0.505	-3.51	-0.344	-4.85	-0.606	-21.45	-18.99
Two or more Vehicles and single-family residence	-1.207	-8.32	-0.892	-12.58	-1.259	-26.21	-21.85
One Vehicle and multi-family residence	-0.653	-5.43	-0.564	-10.57	-0.648	-23.19	-20.01
Two or more Vehicles and multi-family residence	-0.608	-3.79	-0.383	-5.41	-0.597	-20.69	-18.27
ρ	--	--	0.562	2.24	0.895	2.02	1.96
κ_1 (pro-environment attitude)	--	--	--	--	0.883	2.79	2.66
κ_2 (neo-urban lifestyle propensity)	--	--	--	--	1.151	2.53	2.50

** t-stat corrected for sampling error in latent variable value estimation*

Smart-phone owners are more likely to use shared-mobility services, presumably because such services are often hailed using technology-based platforms like apps and websites. Female smart-phone owners who frequently use apps for deriving travel information are less likely to use shared-mobility services, possibly due to safety considerations and their complex trip-chaining behavior (Garikapati et al., 2014). High vehicle ownership rates, especially for households residing in single-family residences, are associated with low usage patterns. Particularly noteworthy is that model coefficients differ in magnitude amongst the model forms, suggesting models that ignore dependencies may offer erroneous forecasts and impacts of policy instruments. Additionally, coefficients on the non-spatial proximity contributions are of same order of magnitude as spatial effects, and thus cannot be ignored. The positive signs indicate that diffusion effects propagate in both spatial and attitudinal space. ADCLRT test showed the superiority of the SORP with multi-dimensional dependencies over all other models at any level of significance.

4. CONCLUSIONS

Dependency effects arising out of geographical proximity has been the focus of traditional spatial activity-travel behavior models. However, in an era of ubiquitous connectivity and social media platforms, strength of association between decision makers may be influenced by attitudes, preferences, values and perceptions. This paper makes a unique contribution to the literature by proposing an econometric methodology that is capable of simultaneously accounting for spatial and non-spatial (attitudinal) dependency effects and disentangle diffusion effects along each dimension. The GHDM-SORP model system is applied to study of frequency of shared-mobility services. The results show that non-spatial dependency effects are significant in explaining the usage patterns of these services and ignoring them could result in erroneous assessment of impacts. Through such mechanisms, agencies and policy makers may effectuate desired changes in behavior in response to various strategies by leveraging the power of diffusion effects that influence people’s travel behavior.

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