

ANALYSIS OF THE IMPACT OF TECHNOLOGY USE ON MULTI-MODALITY AND ACTIVITY-TRAVEL CHARACTERISTICS

Sebastian Astroza

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA
Tel: 512-471-4535; Email: sastroza@utexas.edu

Venu M. Garikapati

Arizona State University
School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85281, USA
Tel: 480-522-8067; Email: venu.garikapati@asu.edu

Chandra R. Bhat (*corresponding author*)

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA
Tel: 512-471-4535; Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Ram M. Pendyala

Arizona State University
School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85281, USA
Tel: 480-727-4587; Email: ram.pendyala@asu.edu

Patrícia S. Lavieri

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA
Tel: 512-471-4535; Email: laviepa@utexas.edu

Felipe F. Dias

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin, TX 78712, USA
Tel: 512-471-4535; Email: fdias@utexas.edu

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ABSTRACT

Smartphone ownership and use is becoming increasingly prevalent in societies around the world. However, very little is known about the impacts of this technology on activity-travel choices. The objective of this study is to determine the extent to which smartphone ownership and use influence activity-travel demand, after controlling for other lifestyle and demographic attributes. The impacts of smartphone ownership and use on multiple travel dimensions are examined through the specification and estimation of a joint model system that explicitly accounts for self-selection effects arising from lifestyle preferences (such as green lifestyle propensity and technology-savviness). In particular, the impacts of smartphone ownership and use on the following choice dimensions are estimated: (a) use of multiple modes of transportation; (b) pursuit of complex trip chains with a large number of intermediate stops; (c) engagement in tours that have a recreational activity; and (d) participation in joint tours that involve an accompanying person. Travel survey data from the 2014-2015 Puget Sound Regional Travel Study is used. The results show substantial and statistically significant effects of smartphone ownership/use on activity-travel patterns, even after controlling for lifestyle preferences. Smartphone ownership and use is found to increase the likelihood of using multiple modes of transportation, and participating in complex tours, joint tours, and recreational tours.

Keywords: smartphone ownership, smartphone use, technology savviness, activity-travel characteristics, tour attributes, latent factors, mixed dependent variables, structural equations models.

1. INTRODUCTION

It would be an understatement to say that technology has become an indispensable and ubiquitous part of human existence everywhere. Smartphones, GPS navigation devices, Bluetooth devices, tablets, phablets, and other mobile wireless devices are being used by people of all walks of life around the world. Recent statistics suggest that more than 90 percent of all adults in the United States have a cellular telephone, with 70 percent of these individuals owning a smartphone (1). Several other developed countries, such as Australia, Canada, and Ireland, exhibit similar smartphone ownership rates (1). Even in emerging economies of the world such as Chile, Malaysia, Lebanon, and China, the smartphone ownership rate is at over 50 percent of the adult population (2). It is also noteworthy that a majority of children, even as young as four years old, own and use smartphones on a regular basis (3).

The pervasive use of technology has undoubtedly affected how people work, shop, play, and communicate (4). The smartphone, and the many apps that are available to fulfill a plethora of purposes, has especially created numerous opportunities for individuals to accomplish many an activity on-the-fly, obtain information in real-time, and take advantage of services at the push of a button. People use smartphone applications throughout the day for getting directions, checking on the status of family and friends through social media, reading news, finding reviews about establishments and businesses, and using ride-sourcing services such as Uber and Lyft, and car-sharing services such as Zipcar.

This paper focuses on the influence of smartphone ownership and use on activity-travel patterns and choices. Although there are a number of technological platforms that influence activity-travel demand, the smartphone is clearly the instrument that has become commonplace in the human ecosystem. Despite the widespread presence of smartphones in societies around the world, very little is known about the influence of smartphones on activity-travel patterns. It may be conjectured that the use of the smartphone (and the many apps) facilitates a flexible mode use pattern, allows individuals to make activity-travel decisions on-the-fly, motivates the formation of more complex tours as individuals seek to explore new opportunities and meet-up in real-time, and results in a re-distribution of participation in activities (trips) of different purposes.

In this paper, hypotheses regarding the influence of smartphones on activity-travel patterns are tested using data collected in the 2014-2015 Puget Sound Regional Travel Study. The Generalized Heterogeneous Data Model (GHDM) developed by Bhat (5) is used to simultaneously model a number of endogenous outcomes capturing smartphone ownership and use, and activity-travel choices including tour complexity, activity (trip) generation by purpose, and mode use. The paper seeks to determine the impact of smartphone use on activity-travel characteristics while explicitly controlling for self-selection (lifestyle preference) effects. In the absence of adequately controlling for such lifestyle effects, impacts of smartphone use on activity-travel demand may be estimated incorrectly.

The remainder of the paper is organized as follows. The next section provides a brief discussion and review of potential smartphone impacts on activity-travel patterns. The third section describes the behavioral framework adopted for this research exercise. The fourth section presents a description of the data set, the fifth section offers a discussion of estimation results, and the sixth section presents an estimation of effects inferred from the model system. The seventh and final section offers concluding thoughts.

2. SMARTPHONE AND TRAVEL: THE CONNECTION

The availability of smartphones and a plethora of apps has made it possible to plan and undertake activities and trips in a more flexible and dynamic (spur-of-the-moment) way. Despite the widespread adoption of smartphones, there is considerable variation in the use of the technology (6). Some may use the smartphone merely for communication and internet browsing, while others may use a number of different apps available on the smartphone to fully exploit the features and capabilities of the technology. The degree to which individuals embrace and utilize technology for various purposes may be regarded as a measure of their “technology savviness”.

Individuals with a high degree of technology savviness, i.e., tech-savvy people, may utilize the capabilities of the technology to adapt their travel choices based on the contextual situation. Depending on the prevailing network condition and real-time travel information about various modes, individuals may choose the mode that they consider most appropriate given prevailing time-space constraints, cost considerations, and modal level of service. Millennials, having been born and brought up in an era of technology and social media, are generally considered more technologically adept. Garikapati et al. (7) note that millennials are more inclined to multi-task than prior generations, and this may also play a role in the choice of mode as “digital natives” may value the ability to use technology platforms for a variety of purposes while traveling. Technology-based multitasking is difficult to accomplish when driving a private automobile. Thus the first hypothesis of this study is that tech-savvy individuals who own and use a smartphone exhibit a greater level of heterogeneity in mode choice.

As smartphones facilitate instant communication, messaging, and social media posts, individuals can arrange to meet-up instantly and undertake joint activities and/or trips with virtually no advance planning required (8). While individuals may have been tempted to keep trip chains simple and access only familiar destinations in the absence of information at their fingertips, it is entirely possible that the assistance of smartphone apps entices individuals to experiment and seek variety, thereby leading to the formation of more complex trip chains. Thus, the second hypothesis studied in this paper is that tech-savvy individuals who own and use a smartphone exhibit more complex trip chains with a larger number of stops and a greater level of activity accompaniment.

The third aspect of interest in this paper is that of activity generation or trip generation, which are treated synonymously as only out-of-home activity engagement is considered. The use of technology may substitute for some travel; for example, telecommuting may substitute for work travel, online shopping or banking may substitute for personal errands, and social media usage may substitute for some face-to-face social visits. The ability to engage in virtual mobility is naturally correlated to the degree of tech-savviness that individuals possess (9). As technology apps provide information about new and exciting destinations, special deals, and entertainment opportunities, it is possible that tech-savvy individuals will undertake additional activities and travel (8). Thus, the third hypothesis is that tech-savvy individuals who own and use a smartphone exhibit a greater level of activity or trip generation for various purposes.

By addressing the three hypotheses identified above, this study aims to shed considerable light on how smartphone ownership and use, and associated latent lifestyle preferences and attitudes, is affecting people’s activity-travel choices. Many transportation planning models that are used for long range transportation planning, infrastructure investment decision-making, and policy formulation do not explicitly consider the effects of technology use on activity-travel demand. The modeling effort undertaken in this paper is aimed at providing new insights that can

be used to enhance multimodal transportation planning models so that they account for technology effects while controlling for latent lifestyle preferences.

3. BEHAVIORAL FRAMEWORK

A simplified representation of the behavioral framework adopted in this paper is shown in Figure 1. There are two latent lifestyle factors that are considered within this study. By including such latent constructs in the behavioral framework, it is possible to account for self-selection effects and isolate or compute the true effect of technology ownership and use on activity-travel choices. The two latent constructs considered in this paper are green lifestyle propensity and technology-savviness. These are factors that have been identified in the literature as being significant and relevant in explaining transportation choices (10). The green lifestyle propensity captures the extent to which an individual is environmentally conscious and attempts to engage in activity-travel patterns and make travel choices that are energy efficient and environmentally friendly. The survey data set used in this study has three ordinal variables that may be considered indicative of a green lifestyle propensity. They are:

- Importance of a walkable neighborhood and being close to activities in choice of home location, (measured on a five-point scale, “very unimportant” to “very important”)
- Importance of being close to public transit in choice of home location, measured on a five-point scale (“very unimportant” to “very important”)
- Importance of being within a 30-minute commute to work in choice of home location, measured on a five-point scale (“very unimportant” to “very important”)

Similarly, there are three variables that represent technology savviness. The tech-savvy construct is represented by two ordinal variables and one binary (nominal) variable as follows:

- Intensity of use of smartphone apps to obtain travel information, measured on a seven-point scale
 - Never
 - Less than once a month
 - A few times per month
 - One day per week
 - 2-4 days per week
 - 5 days per week
 - 6-7 days per week
- Intensity of use of websites (accessible via smartphone, tablet, or computer) to obtain travel information, measured on the same seven-point ordinal scale
- Smartphone ownership, measured as a binary variable indicative of ownership

The extent to which an individual is flexible with respect to their mode usage is treated as a measure of “multi-modality”. The transportation modes included in the survey questions are car (driver or passenger), transit, bicycle (personal or bike-sharing), walking, car-sharing (e.g., ZipCar), and ride-sourcing (e.g., Uber and Lyft). If an individual indicated that he or she is a regular user of a mode or used a mode within the last 30 days, then the individual was considered a user of that mode. A limited-count variable (taking the values between 1 to 6 for any given individual) was then constructed depending on the number of modes used by the individual to represent “multi-modality”. Since this is a limited-count variable, it can be treated in exactly the same way as an ordinal variable with six categories.

Three other endogenous outcomes included in the behavioral framework are descriptors of activity-travel characteristics. The average number of stops per tour, which is a measure of tour

complexity, is treated as a continuous endogenous variable. Tour accompaniment is a binary variable indicating whether the individual pursues all tours during the survey day alone or whether at least one of the tours is undertaken with another individual (household or non-household member). A final binary dependent variable captures whether or not an individual participates in a tour with a recreational stop on the survey day.

In summary, the simultaneous equations model system developed in this paper has six ordinal variables, one continuous variable, and three binary dependent variables. Modeling such a system of equations simultaneously recognizes that individuals often exercise a bundle of choices together consistent with their lifestyle preferences, attitudes, and values. Given the mixed assortment of endogenous variables in the system of equations, the GHDM methodology developed by Bhat (5) is employed to jointly estimate the parameters. The proposed model system offers consistent parameter estimates and more accurate statistical inferences in comparison to an independent set of equations estimated separately. Additional details on the GHDM formulation, including the model set-up, sufficiency conditions for identification of model parameters, and the Maximum Approximate Composite Marginal Likelihood (MACML) estimation approach for the formulation may be found in Bhat (5). It should be noted that the directionality and magnitude of effects of variables in Figure 1 among the endogenous outcomes of interest represent “cleansed” effects after accommodating unobserved covariance effects through the two latent variables of green lifestyle propensity and tech-savviness. The directions of the effects among these endogenous variables were determined after an extensive testing of various model specifications, and choosing the specification that provided the best data fit and behaviorally intuitive interpretation. The fact that the intensity of use of smartphone (for travel information) is predicated on ownership of a smartphone is recognized in the estimation process. Also, a smartphone owner may never use the smartphone for obtaining travel information, even if s/he uses the smartphone to obtain other types of information (regarding events and locations, for example). Finally, reverse endogenous effects reflecting the possibility that the desire to use multiple modes may engender smartphone ownership and use were tested, but the data fit clearly suggested that smart phone ownership and use influenced activity-travel choices rather than the other way.

4. DATA DESCRIPTION

The data for this study is derived from the Puget Sound Regional Travel Study in which travel survey data was collected from a sample of households in the region in 2014 and 2015. The survey collected detailed information about socio-economic and demographic characteristics of all persons in the households that responded to the survey. Travel diary data for a weekday (Tuesday, Wednesday, or Thursday) was collected for all individuals aged 5 years and over in each household. In addition, respondents were asked to provide information about their typical activity-travel patterns. The unique aspect of the survey is that it included a number of questions about attitudes and values in terms of residential location choice, intended adoption and use of autonomous vehicle technologies in the future, and experience with use of car-sharing and ride-sourcing services. In order to have a comprehensive data set suitable for model development in this study, the two years of data were pooled and treated as a single cross-sectional data set. Variables not available in the 2014 data set were imputed based on information available in the 2015 data set. Pooling the 2014 and 2015 data sets was considered appropriate as there were no appreciable changes in system conditions between the two years. There were no significant modal investments or changes in land use, and travel demand (i.e., traffic volumes, vehicle miles of travel,

and transit ridership) remained largely unchanged between 2014 and 2015 (11). The subset of households that responded in both years constitutes the sample of interest in this paper.

After extensive cleaning and filtering, the final sample used for model development and estimation in this paper comprised 1,371 adults. Among these individuals, 57 percent are female, 19 percent are 18-34 years old, 25 percent are 65 years or over, 48 percent are full-time workers, 8 percent are part-time workers, 92 percent have driver's licenses, 40 percent have an undergraduate degree, and 30 percent have a graduate degree. With respect to vehicle ownership, 14 percent of the households live in zero-car households, 44 percent live in one-vehicle households, and 30 percent reside in two-vehicle households (11).

Table 1 provides a summary of the dependent variable characteristics. On average, there are just about two stops per tour. With respect to smartphone and website use, there was considerable difference in the level of use of these respective technologies, largely attributable to the fact that 42 percent of the sample does not own a smartphone to begin with. The multi-modality measure shows that only a small fraction of the sample (6.6 percent) is uni-modal (i.e., exclusively using one mode). Similarly, only small fractions of individuals use five or six modes of transportation (7.3 and 2.1 percent respectively). It was found that only 40 percent of the individuals pursued at least one tour with a recreational activity or stop, which is consistent with the weekday nature of the sample.

5. MODEL ESTIMATION RESULTS

This section presents a detailed discussion of the model estimation results focusing on both the structural and measurement equation components.

5.1 Estimation Results for Structural Equation Component

Table 2 presents results of the structural equation component of the model system. In general, it is found that those who exhibit a greater preference or proclivity towards a green lifestyle are younger, lower-income, and more highly educated. All of these findings are consistent with expectations and earlier findings reported in the literature. Dunlap and York (12) reported a negative effect of income on environmental sensitivity; they argue that a higher level of concern for the environment among lower income households may be attributable to their experiencing the consequences (e.g., health) associated with environmental deterioration. The model also shows that women are more likely than men to be interested in a green lifestyle, consistent with findings from previous studies (13, 14).

The model results show that tech-savvy individuals are young, more educated, higher income, do not have children, and predominantly workers (full-time, part-time, or self-employed). In general, younger individuals (millennials, for example) grew up in an era of technology, ubiquitous connectivity, and social media, thus rendering them tech-savvy (15). Similarly, it has been found that education is associated with a greater level of awareness and knowledge in using technology (16), and the model estimation results in this paper are consistent with this notion.

It is found that the green lifestyle propensity and technology savviness constructs are significantly correlated with one another. The positive correlation of 0.134 is found to be statistically significant at the 0.05 level, indicating that those who are technology savvy are also more likely to prefer a green lifestyle and vice-versa.

5.2 Estimation Results for Measurement Equation Component

Estimation results for the measurement equation component of the model system are shown in Tables 3 and 4. Table 3 presents results for ordinal indicators considered in this study, including importance of neighborhood walkability, proximity to transit, and commute time considerations in choice of residential location. Ordinal variables included in Table 3 also include the intensity (frequency) of use of smartphone apps or websites for travel information, as well as the binary variable corresponding to smartphone ownership.

Higher income individuals are more likely to own a smartphone, as evidenced by the negative coefficients associated with all income categories included in the model. Younger individuals are more likely to own smartphones, consistent with the notion that digital natives embrace the latest technology (16). Those who have a smartphone are more likely to use websites for travel information, at least partly because access to a smartphone also provides instant access to websites.

The indicators used in this study are strongly associated with the latent lifestyle constructs. Green lifestyle propensity is associated with the importance that people attach to living in a walkable neighborhood, close to transit service, and within a 30-minute commute to work. On the technology side, the intensity of web use for travel information, intensity of smartphone app use for travel information, and the ownership of a smartphone itself are all significantly related to the technology savviness construct.

The ordinal variable considered in Table 4 is that of the multi-modality measure. Estimation results indicate that people with a higher income are more likely to be “multi-modal” in their transportation choices; the coefficients reveal a very intuitive progression in numerical value from the lowest income category to the highest income category. Higher vehicle ownership is associated with a more “uni-modal” pattern; it is likely that households that have sunk resources into a high level of vehicle ownership tend to be more exclusively car-oriented in their mode choice.

Among four characteristics, it is found that the likelihood of engaging in a recreational tour increases with income. Workers (of all types), relative to non-workers, are more likely to engage in multi-stop tours, presumably due to trip chaining during the commute. A higher level of vehicle ownership is associated with more complex tour-making and tour accompaniment, a finding consistent with expectations. Those with children are less likely to engage in recreational tours, possibly because of time-space constraints (17).

The two lifestyle constructs are important predictors of activity-travel choices. Green lifestyle propensity is significantly associated with multi-modality, as expected. Those who are more environmentally conscious are likely to use alternative modes of transportation to reduce their carbon footprint. Those who are technology-savvy are similarly more multi-modal, more likely to engage in complex tours with a larger number of stops, more likely to engage in tours that involve accompaniment, and more likely to engage in recreational tours. This result is important, and clearly indicates that the intrinsic (and stochastic) tech-savvy personality factor leads to a higher likelihood of owning a smartphone, increases the intensity of use of smartphones and web services for obtaining travel information, and also positively affects all of the activity-travel choice dimensions considered in this paper. That is, there are self-selection effects characterizing the relationship between smartphone ownership and use the one hand, and activity-travel choices on the other. If self-selection effects captured by the inclusion of the tech-savviness factor are ignored, “spurious” causal inferences (in the present case, exaggerated positive impacts) of the effects of electronic gadget ownership and use on activity-travel choices may be drawn.

Finally, Table 4 shows the “true” endogenous effects that are significant in the model system *after accounting for unobserved effects that are captured in the latent lifestyle constructs*. It is found that smartphone ownership significantly affects activity-travel choices; smartphone ownership is associated with multi-modality, complex tour-making, tour-making that involves accompaniment, and recreational tours. The intensity of use of technology has slightly different effects. The use of websites is associated with multi-modality and tour complexity, possibly because individuals use information on the web to learn about transit schedules, bicycle and walking paths, and alternative destinations. Consistent with expectations, recreational tour participation is positively associated with tour complexity and tour accompaniment.

All of the significant relationships are depicted in Figure 1 to illustrate the jointness in relationships embedded in the model system. In addition to estimating a joint model system that accounts for latent lifestyle constructs (unobserved factors) and error covariances, an Independent Heterogeneous Data Model (IHDM) was also estimated. This model does not consider the jointness across endogenous outcomes (i.e., the covariances and self-selection effects engendered by the stochastic latent constructs in the GHDM are ignored). Three of the six ordinal variables used in the GHDM are included solely for the purpose of model identification and do not serve any purpose in predicting the choice bundle once the model is estimated (these are identified as “ordinal indicators” in Table 3). The non-nested likelihood ratio test can be used to compare the goodness-of-fit of the two models for the seven endogenous outcomes identified in Figure 1. Details on computing the predictive log-likelihood values of the models, and how these can be used to test if the adjusted likelihood ratio indices of the two non-nested models are significantly different, are provided in Bhat et al. (14). The adjusted likelihood ratio indices of the GHDM and IHDM with respect to the log-likelihood with only constants are 0.5107 and 0.2663 respectively.¹ The non-nested adjusted likelihood ratio test returns a value of $\Phi(-90.1)$, which is literally zero, clearly rejecting the IHDM in favor of the GHDM. To ensure that the superior data fit of the GHDM is not simply an artifact of overfitting on the estimation sample, the goodness-of-fit of the GHDM and IHDM was evaluated for various market segments of the estimation sample. The results clearly indicate that the GHDM is better able to replicate observed patterns in the data, both for the full sample as well as for each market segment. Additional details regarding the comparative assessment are provided in Astroza et al. (2016).

6. COMPUTATION OF TECHNOLOGY EFFECTS

The objective of this section is to present the “true” effects of technology (smartphone ownership and use) on activity-travel characteristics. The GHDM serves as a rigorous platform to compute the true effects of technology ownership and use on activity-travel behavior while controlling for unobserved self-selection effects. In the IHDM, exogenous variables used to explain lifestyle constructs are simply entered directly into the choice equations; in other words, self-selection effects are ignored in the IHDM. Thus, it is possible to compute the true effects of technology ownership and use by comparing the magnitude of effects provided by the GHDM and IHDM respectively. While the magnitude of effect computed from the IHDM includes both the technology effect and the unobserved self-selection lifestyle effect, the magnitude of effect computed from the GHDM reflects only the true technology effect while controlling for the unobserved lifestyle effect. Table 5 presents the results of this comparison. To generate this table,

¹The GHDM has 111 parameters with a predictive log-likelihood value at convergence of -8,077.56. The IHDM has 166 parameters with a predictive log-likelihood value at convergence of -12,113.30. The predictive log-likelihood value at constants is -16,737.81.

the average treatment effect (ATE) is computed using both model forms. The ATE is a measure of the expected change in the dependent variable for a change in the discrete or ordinal independent variable. Methodological details on the computation of ATEs are presented in Astroza et al. (11).

The table shows the effects computed when a random individual in the data set shifts from a status of “does not own a smartphone” to a status of “owns a smartphone”. A new smartphone owner is more likely to become multi-modal, engage in complex tours with larger number of stops, engage in tours with accompaniment, and engage in recreational tours. All of these effects are similar in sign between the GHDM and IHDM, but the magnitude of the effect is consistently smaller in the GHDM.² This is because the magnitude of the effect implied by the IHDM includes the unobserved lifestyle effect. The differences are statistically significant at the 0.1 level for many of the effects (marked with an asterisk). These differences allow an isolation of the true effect of technology ownership from the unobserved lifestyle effect. It is found that a majority of the effect is attributable to technology ownership, suggesting that technology plays a substantial and significant role in shaping activity-travel patterns.

Next, the table shows the effect of converting a random individual in the data set from a status of “does not own or use a smartphone for travel information” to a status of “owns and uses a smartphone for travel information”. It is found that the effects from both the GHDM and IHDM are larger in the case where an individual transitions to smartphone ownership and use (relative to a change in smartphone ownership alone); this is to be expected as ownership and intensity of use is likely to have a larger effect on activity-travel choices than ownership alone. Again, the IHDM overestimates the impacts because it ignores self-selection effects. Further unraveling of the technology effects (last column panel of Table 5) shows that it is the ownership that accounts for the bulk of the technology effect. This suggests that the ownership of a smartphone engenders change by nature of the connectivity and access to information that it provides. The magnitude of the effect is then amplified further depending on the level or intensity of use to obtain travel information.

7. CONCLUSIONS

The impact of information and communication technologies on traveler behavior is of considerable interest, particularly with the rapid penetration of smartphones in the market. Although smartphones are changing the way people communicate, access information, travel, choose destinations, and schedule activities, there is very little knowledge of the impacts of this technology on activity-travel demand. As a result, travel forecasting models that are used to plan transportation infrastructure investments largely ignore the effects of technology on activity-travel choices. An important facet of understanding and quantifying the effect of smartphone (or any technology) ownership and use on travel demand is the need to control for unobserved lifestyle preferences that may lead to the presence of self-selection effects. Any model that purports to account for technology impacts on traveler choices should recognize (to the extent possible) that individuals are often exercising a bundle of choices together, thus calling for the specification and estimation of simultaneous equations model systems that capture jointness in decision-making

²The magnitudes of the average ATE in Table 5 may be interpreted as follows; the first ATE value corresponding to the multimodality measure indicates that a random individual who acquires a smart phone is, on average, likely to increase her or his probability of using six modes by 0.13. Equivalently, if 100 random individuals acquire smartphones, the point estimate indicates that 13 more of them will use six modes than earlier; other values may be similarly interpreted.

while accounting for common unobserved factors that simultaneously impact multiple choice dimensions.

This study uses data from the 2014-2015 Puget Sound Regional Travel Study to quantify the impacts of smartphone ownership and use on activity-travel choices, while explicitly accounting for self-selection effects arising from unobserved latent lifestyle preferences. Two latent constructs, representing green lifestyle propensity and technology savviness, which represent unobserved inherent lifestyle preferences are incorporated in the model system. Endogenous variables of interest include the extent to which an individual uses multiple modes of transportation, complexity of tour making (in terms of number of stops per tour), participation in joint tours, and engagement in tours with a recreational activity or stop. Given the mixed nature of the endogenous variables in the model, the Generalized Heterogeneous Data Model is used to jointly estimate parameters.

It is found that a number of socio-economic and demographic variables such as age, gender, income, education, and work status are significant predictors of lifestyle preferences, with younger, educated, and high income individuals more likely to adopt green lifestyles and be technology savvy. Those with a green lifestyle propensity are found to reside in locations that are more walk and transit friendly, while those who are technology-savvy are found to use websites and smartphone apps to access travel information. More importantly, even after controlling for these latent lifestyle constructs, model estimation results show that individuals with access to a smartphone make different activity-travel choices than individuals who do not have such access. In particular, the study results show that smartphone ownership and use is associated with the use of multiple modes of transportation, pursuit of more complex tours with a larger number of stops per tour, engagement in recreational tours, and participation in joint tours with an accompanying person.

The analysis shows that the ownership of a smartphone, by itself, contributes to a significant difference in activity-travel choices with the intensity of use of the smartphone to obtain travel information further amplifying the effect. The unobserved lifestyle effect is also significant, clearly indicating the presence of self-selection effects that should be recognized in modeling efforts that aim to reflect the impacts of smartphone connectivity and use on travel behavior. As technology becomes increasingly pervasive and smartphone penetration rates continue to rise, it is imperative that travel forecasting models incorporate technology effects to predict travel demand under a variety of alternative future scenarios. From an empirical perspective, the model presented in this paper can be extended to consider additional variables such as participation in tours whose primary activity purpose is other than recreation, alternative measures of tour complexity, and/or tour mode. It may also be of value to perform analysis with more disaggregate data regarding smartphone and website usage. Such detailed information could not be used in the current modeling exercise due to data limitations. Hourly or daily data on smartphone app or website use would facilitate the development of models that uncover the direct effects of technology use on individual's tour- and trip-level travel decisions such as mode choice or activity location choice. These remain directions for future research.

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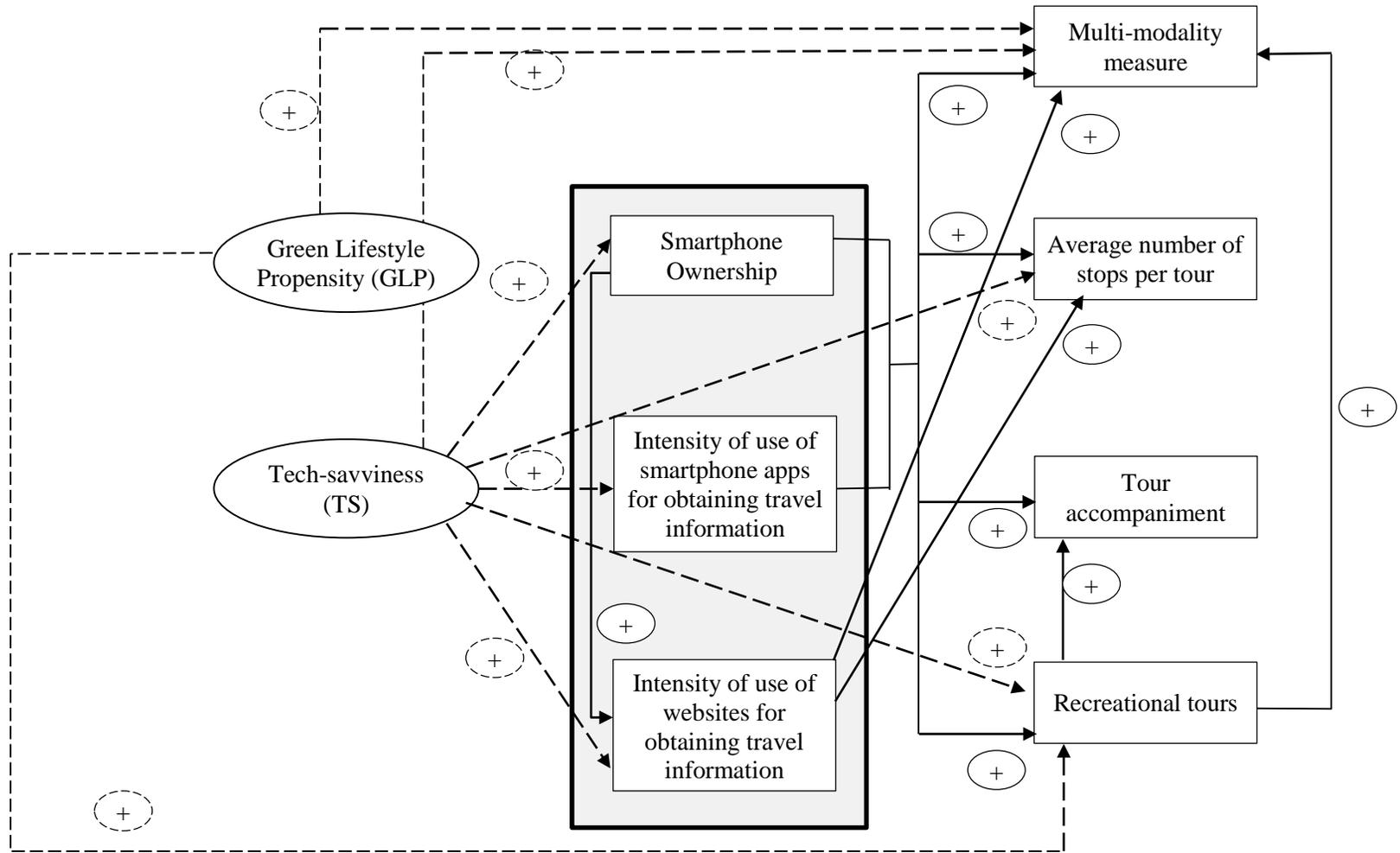
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- - -> : Impact of a latent construct on an endogenous outcome
 - - -> (+) : Endogenous effect of one outcome on another

FIGURE 1 Behavioral framework: Effects of latent constructs and endogenous outcomes.

TABLE 1 Sample Characteristics of Dependent Variables

Dependent variable: Continuous variable							
Variable		Mean	Std. Dev.	Min.	Max.		
Average number of stops per tour		2.08	1.54	1.00	10.00		
Indicator variable: Ordinal variables							
Attitudinal Question		Response rate					
		Very Unimportant 1	2	3	4	Very Important 5	
<i>How important when choosing current home:</i> Having a walkable neighborhood and being near to local activities		7.2%	6.1%	10.4%	30.0%	46.3%	
Being close to public transit		15.5%	10.6%	14.2%	22.3%	37.4%	
Being within a 30-minute commute to work		11.3%	6.4%	16.0%	20.6%	45.7%	
Frequency of use		Response rate					
		Never	Once per week or less		More than once per week		
<i>How often get travel info from:</i> Smartphone apps		60.6%	15.8%		23.6%		
Websites		27.4%	46.9%		25.7%		
Multi-modality measure		Frequency					
		1 mode	2 modes	3 modes	4 modes	5 modes	6 modes
Number		90	322	479	351	100	29
Percentage (%)		6.6	23.5	34.9	25.6	7.3	2.1
Dependent variable: Nominal variables							
Smartphone ownership	Number of observations (%)	Tour accompaniment	Number of observations (%)	Recreational tours	Number of observations (%)		
Has a smartphone	791 (57.7)	Individual makes all tours alone	810 (59.1)	Individual makes no recreational tours	830 (60.5)		
Does not have a smartphone	580 (42.3)	Individual makes at least one tour with accompaniment	561 (40.9)	Individual makes at least one recreational tour	541 (39.5)		

TABLE 2 Estimation Results of Structural Equation Component

Variable	Green Lifestyle Propensity (GLP)		Tech-savviness (TS)	
	Coefficient	t-stat	Coefficient	t-stat
<i>Household income (base: 100,000 or more)</i>				
Less than 35,000	0.702	8.91	-0.588	-11.93
35,000 – 49,999	0.391	6.72	-0.285	-8.00
50,000 – 74,999	0.164	5.33	-0.372	-7.92
75,000 – 99,999	0.111	6.15	-0.150	-6.42
<i>Age (base: 65 years or older)</i>				
18 to 34 years old	0.716	8.74	1.501	3.23
35 to 44 years old	0.489	6.09	1.270	3.16
45 to 54 years old	0.235	4.44	0.773	3.28
55 to 64 years old	0.180	2.01	0.359	2.16
<i>Gender (base: female)</i>				
Male	-0.112	-2.12	--	--
<i>Educational attainment (base: less than a bachelor's degree)</i>				
Bachelor's degree	0.158	4.28	0.193	3.10
MS or PhD degree	0.302	3.67	0.258	2.58
<i>Work status (base: unemployed)</i>				
Full-time worker	--	--	0.192	2.17
Part-time worker	--	--	0.231	2.02
Self-employed	--	--	0.221	1.99
<i>Presence of children in the household (base: no children)</i>				
At least one child in the household	--	--	-0.321	-2.12
Correlation coefficient between 'green lifestyle propensity' and 'tech-savviness' latent constructs	0.134 (t-stat: 4.98)			

TABLE 3 Estimation Results for Ordinal Indicators and Smartphone Ownership/Use Variables of Measurement Equation

Independent Variables	Ordinal Indicators						Smartphone Ownership Use and Website Use Variables					
	Having a walkable neighborhood and being near local activities		Being close to public transit		Being within a 30-minute commute to work		Intensity of use of websites for travel information		Intensity of use of smartphone apps for travel information		Smartphone ownership (base is “non-smartphone owner”)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
<i>Constants</i>	1.440	5.02	0.993	3.93	1.402	7.48	1.379	7.21	1.004	3.86	0.578	2.04
<i>Thresholds for ordinal indicators</i>												
Somewhat unimportant & not important	0.477	12.38	0.416	13.20	0.382	17.34	-----	-----	-----	-----	-----	-----
Not important & somewhat important	0.817	15.12	0.877	20.00	0.724	12.09	-----	-----	-----	-----	-----	-----
Somewhat important & very important	1.683	13.65	1.544	12.07	1.411	13.20	-----	-----	-----	-----	-----	-----
<i>Threshold for intensity of use to acquire travel info.</i>												
Low intensity & high intensity	-----	-----	-----	-----	-----	-----	0.563	2.66	0.462	3.04	-----	-----
<i>Household Income (base is 100k or more)</i>												
Lower than 35k	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-0.157	-2.45
Between 35k and 50k	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-0.103	-2.65
Between 50k and 75k	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-0.096	-2.51
Between 75k and 100k	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-0.032	-2.88
<i>Age (base is 35 years or older)</i>												
Between 18 and 34 years old	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	0.264	5.34
Full-time, part-time or self-employed worker	-----	-----	-----	-----	-----	-----	0.097	2.46	-----	-----	0.158	2.16
Presence of children in the HH	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	0.102	1.99
<i>Latent constructs</i>												
Green Lifestyle Propensity (GLP)	0.213	12.80	0.279	11.11	0.302	12.28	-----	-----	-----	-----	-----	-----
Tech-savviness (TS)	-----	-----	-----	-----	-----	-----	0.293	3.26	1.284	12.65	0.403	7.32
<i>Endogenous Effects</i>												
<i>Smartphone ownership (base is “does not have a smartphone”)</i>												
Has a smartphone	-----	-----	-----	-----	-----	-----	0.197	2.10	-----	-----	-----	-----

TABLE 4 Estimation Results for Multi-modality and Tour Characteristic Variables of Measurement Equation Component

Independent Variables	Ordinal Variable		Tour Characteristic Variables					
	Multi-modality measure		Average number of stops per tour*		Tour accompaniment (base is “all tours alone”)		Recreational tours (base is “no recreational tours”)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
<i>Constants</i>	2.585	5.01	1.937	6.58	1.264	4.00	1.031	2.25
<i>Thresholds for ordinal variable</i>								
2 modes & 3 modes	0.327	11.99	-----	-----	-----	-----	-----	-----
3 modes & 4 modes	0.698	12.15	-----	-----	-----	-----	-----	-----
4 modes & 5 modes	1.002	12.32	-----	-----	-----	-----	-----	-----
5 modes & 6 modes	1.367	11.01	-----	-----	-----	-----	-----	-----
<i>Household Income (base is 100k or more)</i>								
Lower than 35k	-0.416	-2.65	-----	-----	-----	-----	-0.126	-2.34
Between 35k and 50k	-0.357	-3.01	-----	-----	-----	-----	-0.101	-3.07
Between 50k and 75k	-0.305	-2.95	-----	-----	-----	-----	-0.054	-2.24
Between 75k and 100k	-0.231	-2.44	-----	-----	-----	-----	-0.023	-3.00
Full-time, part-time or self-employed worker	-----	-----	0.436	3.43	-----	-----	0.158	2.16
Number of vehicles in the HH	-0.635	-2.74	0.227	2.66	0.369	3.97	-----	-----
Presence of children in the HH	-----	-----	-----	-----	0.893	5.23	-0.129	-2.34
Individual living alone	-----	-----	-----	-----	-0.047	-1.97	0.268	2.73
Has a driver’s license	0.587	2.67	-----	-----	-----	-----	-----	-----
<i>Latent constructs</i>								
Green Lifestyle Propensity (GLP)	0.452	4.90	-----	-----	-----	-----	0.322	3.18
Tech-savviness (TS)	0.562	3.12	0.305	2.81	0.142	2.58	0.246	2.47
<i>Endogenous Effects</i>								
<i>Smartphone ownership (base is “does not have a smartphone”)</i>								
Has a smartphone	0.622	7.00	0.567	2.54	0.271	3.24	0.195	2.63
<i>Intensity of use of websites for travel info. (base is “never”)</i>								
Once a week or less	0.104	1.99	0.115	2.03	-----	-----	-----	-----
More than once a week	0.173	2.67	0.167	2.39	-----	-----	-----	-----
<i>Intensity of use of smartphone apps for travel info. (base is “never”)</i>								
Once a week or less	0.382	3.69	0.172	2.73	0.100	3.27	0.075	1.99
More than once a week	0.520	3.22	0.219	2.33	0.134	2.90	0.098	1.98
<i>Recreational tours (base is “no recreational tours”)</i>								
At least one recreational tour	-----	-----	0.364	2.19	0.172	2.80	-----	-----

*Estimated variance of average number of stops is 1.276 and the associated t-stat is 3.42. The constant is greater than one and all of the coefficients are positive, which ensures that the model will always predict an average number of stops greater than or equal to one.

TABLE 5 Average Treatment Effects (ATE) of Smartphone Ownership/Use (standard error in parenthesis)

Variable	New Smartphone Owner Scenario				New Smartphone Owner and User Scenario					
	ATE from GHDM	ATE from IHDM	% Difference Attributable to		ATE from GHDM	ATE from IHDM	% Difference Attributable to		% Difference Attributable to	
			“True” Effect	Unobserved Effect			“True” Effect	Unobserved Effect	Smartphone ownership effect	Smartphone use effect
<i>Multi-modality measure</i>										
1 mode	-0.010 (0.002)	-0.013 (0.003)	77	23	-0.015 (0.001)	-0.020 (0.003)	75	25	67	33
2 modes	-0.103 (0.009)	-0.135 (0.015)*	76	24	-0.149 (0.010)	-0.212 (0.017)*	70	30	69	31
3 modes	0.052 (0.006)	0.076 (0.004)*	68	32	0.083 (0.007)	0.100 (0.009)	83	17	63	37
4 modes	0.157 (0.010)	0.218 (0.012)*	72	28	0.204 (0.013)	0.259 (0.018)*	79	21	77	23
5 modes	0.003 (0.001)	0.005 (0.001)	60	40	0.006 (0.002)	0.008 (0.002)	75	25	50	50
6 modes	0.130 (0.010)	0.226 (0.017)*	58	42	0.155 (0.009)	0.194 (0.012)*	80	20	84	16
<i>Average number of stops</i>	0.129 (0.014)	0.153 (0.013)	84	16	0.170 (0.011)	0.206 (0.013)*	83	17	76	24
<i>Tour accompaniment</i>										
All tours alone	-0.097 (0.013)	-0.115 (0.012)	63	37	-0.158 (0.008)	-0.192 (0.017)*	82	18	61	39
At least one tour with accompaniment	0.103 (0.010)	0.153 (0.006)*	67	33	0.139 (0.009)	0.182 (0.008)*	76	24	74	26
<i>Recreational tours</i>										
No recreational tours	-0.125 (0.007)	-0.180 (0.011)*	69	31	-0.157 (0.010)	-0.193 (0.012)*	81	19	80	20
At least one recreational tour	0.104 (0.006)	0.162 (0.008)*	64	36	0.146 (0.012)	0.184 (0.011)*	79	21	71	29

*Difference in ATE between the GHDM and IHDM is significant at the 0.1 level (90% confidence level).