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# "Does Social Networking Substitute for or Stimulate Teenagers' Travel? Findings from a Latent Class Model."

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**Abstract**
The aim of this paper is to investigate and quantify the influence of various social networking (SN) usage styles on adolescents' travel behavior. For this purpose a latent class model is developed, which incorporates SN usage styles as higher-level individual orientations influencing the number of trips made for social purposes. The latent class model consists of two parts: 1. The class membership model, which links the latent SN usage styles to socio-demographic variables; and 2. the class-specific choice model, which is a Poisson regression and shows the influence of an SN usage style and socio-economic variables on the number of trips made for social purposes. The methodology is tested with data from a survey conducted in Cyprus in 2012 and refers only to adolescents. The survey provides data on 15,693 social trips of 9,735 participants (20% of the total high-school population). The class membership model indicates that there are four latent SN usage styles, while the results of the class-specific model indicate that the rational SN usage style (Class 1) and the SN addiction (Class 3) increases the number of social trips, while the indifference in SN usage (Class 2) and non-SN-users (Class 4) affects negatively the number of social trips. The results of the study provide insights into how SN usage affects Net Generations travel behavior, and especially trip substitution vs complementarity, while the class specific model is rich in interpretation, and serves as a harbinger for policy-makers.

*Key words:* Latent Class Model, Poisson Regression, Social Networking, Social Media, Travel Behavior, Trips, Teenagers/ Adolescents, Net Generation.

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## 1. INTRODUCTION

Social media are designed to foster social interaction in a virtual environment and millions of contemporary adolescents use them. Using social media web sites is among the most common activities of today's adolescents. Any web site that allows social interaction is considered a social media site, including social networking (SN) sites such as Facebook, MySpace, and Twitter; gaming sites and virtual worlds such as Second Life, Club Penguin, and the Sims; video sites such as YouTube; and blogs. Members use these sites for a number of purposes. The root motivation is communication and maintaining relationships. Popular activities include updating others on activities and whereabouts, sharing photos and archiving events, getting updates on friends' activities, displaying a large social network, sending messages privately, posting public testimonials and presenting an idealized persona.

This culture of innovation and rapid technological adaptation is particularly strong among the younger generations, especially the New Boomers or Net Generation (born between 1983 and 2001; PRB, 2009). These so-called "internet natives" grew-up in the era of personal computing and the internet or, as per Tapscott (2009), they have been "bathed in bits and bytes" since birth and easily integrate technology into their daily lives. This discourse has a wide social impact and its echoes can be found in psychology, business literature and government policy. The general claim, made in this generation's discourse, is that this material context has led to young people developing a natural aptitude and high skill levels in relation to the new technologies. In contrast, those older people who grew up in an analogue world are portrayed as being always behind, like immigrants to the new world (Tapscott, 2009). It is suggested that these older digital immigrants are never likely to reach the same levels of skill and fluency that have been developed naturally by those who have grown up with the new technologies. Thus, a generational gap is developing.

The emergence of SN has upended the way teenagers interact with each other and the world and there is now little room for doubt about its impact on aspects of social lives such as friendships, information sharing and leisure activities. More than ever before, using social media means creating as well as receiving, with user control extending far beyond the selection of ready-made, mass-produced content. Against this background, in recent years an increasing body of researchers has tried to investigate the kind of activities teenagers conduct using SN and the effects on teenagers' personalities and psychologies. However, little is known about how much, why, and how individuals, and more specifically adolescents, utilize social media, and how its usage affects their travel behavior.

The aim of this paper is twofold. Initially, we investigate the time that teenagers allocate to social media, the gadget ownership, the internet connection patterns and the activities they conduct through SN. Then, we assume that there are various styles of SN usage and that these styles affect in different ways the number of social trips the teenagers make. In doing so, we develop a latent class model, which incorporates SN usage styles as higher-level individual orientations influencing the number of trips made for social purposes. We prefer to investigate only the trips made for social purposes, as we postulate that the trips that teenagers make for schooling and tutorial purposes are not affected by SN. The methodology is tested with data from a large-scale transport survey conducted in Cyprus in 2012 and refers only to adolescents. In cooperation with the Ministry of Education and Culture (MOEC) of Cyprus, the web-based questionnaire was forwarded to all Cypriot high schools and the sample consists of 9,735 participants (20% of the total student population), aged from 12 to 18 years old in 2012 (born 1995-2001; Net Generation). The survey provides data on 15,693 social trips, recorded over a Saturday.

The innovation of this research covers several topics. First of all, to our knowledge it is the first time that such a large-scale survey on travel behavior, focusing only on teenagers, has been conducted. Secondly, the questionnaire used for the data collection was designed specifically to investigate teenagers' perceptions of travel behavior; it was designed not only by transport planners but also by psychologists and economists, with the aim of approaching the multidimensional nature of transportation problems in depth. Third, although the effect of ICT on travel behavior has been widely studied the last decade, there are only few surveys that investigate the effect of the SN usage on travel behavior. Fourth, Net generation behaves in a different way than their parents, thus a generational gap is created which may affect transportation sector as well. Furthermore, the findings of this study offer guidelines to transport policy makers as to how Net Generation uses social media. Finally, the investigation of teenagers' travel behavior may explain many of the trends and undesired behaviors that adults adopt.

The remainder of the paper is structured as follows. Section 2 reviews the literature. Section 3 describes the modeling framework and associated mathematical formulations. The case study, the sample's descriptive statistics and the SN usage patterns are presented in section 4, while section 5 describes the model estimation results. Section 6 concludes the paper by providing a summary of the findings, and implications for policy and further research.

## 2. STATE-OF-THE-ART

### 2.1 Impact of ICT and Social Media on Activities and Travel Behavior

While the technology underlying many of today's popular information and communication technologies (ICTs) has been available since the 1980s or 1990s, they have only started to become mainstream over the past decade, as the costs of computing and internet usage have fallen (Mans et al., 2012; Kamargianni & Polydoropoulou, 2011). High-speed internet access, especially broadband and fiber-optic, has become much more prevalent and the number of people with internet access at home increased from 1.4 billion in 2009 to almost 1.6 billion in 2010, with 65% of these in developed countries (UNSD, 2010).

The importance of technology in our daily lives has increased, and the adoption of ICT has changed the way we live, communicate, work and entertain, and consequently how we travel. ICT provides people with alternatives to face-to-face communication and thus have the potential to substitute for physical travel. In response to this rapid expansion, a new literature has emerged to explain the potential effects of these trends on travel behavior. A vast body of researchers has been investigating the impact of ICT on transportation, examining concepts such as telecommuting/teleworking, e-commerce and time planning. Results on telecommuting and travel behavior vary, with some studies concluding that teleworking substitutes for daily travel (Walls & Safiro, 2004; Choo et al., 2011) and others that teleworking modifies the daily commute (Polydoropoulou & Tsirimpa, 2012). Also, the overall effect of e-shopping on travel behavior remains unclear, with different studies reporting contradictory and ambiguous findings, depending on the type of goods purchased (Farag et al., 2007; Dijst et al., 2008; Papola & Polydoropoulou, 2006; Mokhtarian, 2004). These studies have greatly contributed to our understanding of the possible and potential impacts of ICT on physical travel, which can be grouped into four categories (Mokhtarian, 1990; Mokhtarian, 2004; Pendyala et al., 1991; Salomon, 1986):

1. *Substitution*: usage of technology replaces a physical trip;
2. *Complementarity*: usage of technology creates additional demand for travel;

3. *Modification*: usage of technology does not affect the frequency of physical travel, but may change the characteristics of trips, such as timing and chaining;
4. *Neutrality*: usage of technology is independent of the traditional trip and has no effect on regular trip making.

Although the relationship between ICT and travel patterns has received a substantial amount of attention, not many studies focus on leisure or social travel even though it is the fastest-growing segment of travel (van de Berg et al., 2011; Mokhtarian et al., 2006; Axhausen, 2005). It is highly probable that the effect of ICT on social travel differs from its effect on travel for other purposes, such as work or shopping. Travel behavior is influenced by someone's social network characteristics, as they are relevant to his or her propensity to engage in social activities (Carrasco & Miller, 2006).

According to Mokhtarian et al. (2006), complementarity and modification are more likely than substitution in the case of social activities, because ICT-based alternatives to these activities (if available) are rarely satisfying substitutes. This is confirmed by Senbil and Kitamura (2003), who studied the relations between telecommunication and travel for the three types of activities distinguished by Chapin (1974): 1. mandatory (work and work-related) activities, 2. maintenance activities (grocery shopping, eating, household maintenance, etc.), and 3. discretionary activities (leisure, sports, hobbies, etc.). They found substitution effects for work activities; for maintenance activities, the effect appeared to be neutral, and for discretionary activities they found complementary effects. The complementary effect of ICT on social activities was also identified by Tillema et al. (2007), who found a positive correlation between frequency of face-to-face contacts and electronic communication.

However, the majority of these studies refer to adults (the Baby Boomers Generation), while there is little work, particularly produced by psychiatrists and sociologists, on how young people and teenagers (the Net Generation, or Net Geners) use social media and how this affects their activities and travel behavior. Yet the recent explosion in online SN sites such as Facebook, Twitter, MySpace and others has attracted considerable interest from academia, policy makers, parents and young people themselves, the repeated claim being that something new is taking place (Dwyer, 2007). Teenagers are in the vanguard of SN practices and Facebook statistics show that, in the US, 73% of teenagers belong to a social network, the average teenager has 201 Facebook friends, and 37% send messages to friends more than once on a daily basis (Teen Facebook Statistics, 2012).

Pew Research Center (2010) published statistics showing that almost 80% of American teenagers read interactive blogs daily, leaving comments and adding links. Teenagers are multitaskers, watching TV or studying while chatting with friends and navigating the web. They are more likely than adults to use their cellphones as everything from alarm clocks to GPS devices. They see the computer as more than a tool, as a place to congregate with friends. Their safe communal spaces are not mainly in the physical world, but rather online, on SN sites. Rather than being antisocial, Net Geners are developing an entirely new set of social skills. Also, a research of Pew (2010) showed that today's teenagers act differently in the workforce. They want to work flexibly, in terms of time and place. They want work to be fun and they expect the workplace to emphasize interpersonal relationships (even if they are virtual). Furthermore, recent clinical studies have shown that interaction with computer technology has changed Net Geners' brains (Sternberg & Preiss, 2013; Black, 2010). Net Geners' experience of using multimedia has made them more visually acute and given them better spatial awareness. Video games have benefited them in surprising ways. They have better hand-eye coordination, and are more effective decision makers and collaborators (O'Keefe & Clarke Pearson, 2011).

With this context in mind, it is crucial to study Net Geners' travel behavior as well. As the increasing popularity of social media has impacts on teenagers' lifestyles and daily lives, including aspects such as friendships, information sharing and their social lives, it is expected that it will affect their travel and trip-making behavior too.

**2.2 Latent Class Models (LCMs)**

The LCM for the analysis of individual heterogeneity has a history in several literatures. LCMs were introduced by Lazarsfeld (1950) and since then there have been significant contributions in terms of estimation methods, types of data and the complexity of the models, made by Goodman (1974), Haberman (1979), Hagenaars (1990), and Vermunt and Magisdon (2000). Widely used in the social sciences, latent class analysis is based on the theory that individuals differ in their behaviors due to some unobservable latent trait. Social scientists are often interested in relating latent traits to some other variables, with the ultimate purpose of understanding what defines or perhaps causes the latent traits (Nagin et al., 1995).

The first aim of latent class analysis is to identify the number of classes required to explain the associations among the observed variables, and the second is to allocate respondents/objects to latent classes. Therefore, latent class analysis has a lot of things in common with classification methods for multivariate data, such as cluster analysis, multidimensional scaling and correspondence analysis. The main difference from the aforementioned techniques is that latent class analysis is a model-based approach that can be used for any type of data and allows the appropriateness of the model to be tested statistically. The other methods are mainly based on measures of differences and similarities, and in some cases they have limited practical use.

Latent class modeling assumes that the population can be segmented into a finite number of groups, or classes, according to some combination of characteristics. The individuals within each of the groups share similar characteristics and are dissimilar from those in other groups according to those same characteristics (Coogan et al., 2011). The LCM, which specifies random parameters that follow a continuous joint distribution, assumes that a discrete number of classes are sufficient to account for preference heterogeneity across classes. Therefore, the unobserved heterogeneity is captured by these latent classes in the population, each of which is associated with a different parameter vector in the corresponding utility function.

Class membership is assumed to be probabilistic so each individual can, in theory, possess characteristics of each class to varying degrees according to their class membership probabilities. Standard statistical tests can be used to determine the most appropriate number of segments that should be used to classify the population according to the characteristics selected for the segmentation. Once the classes have been defined, the members of those classes can be profiled, along with the characteristics used to define the classes as well as any other variables that are not used to define the classes.

In the last few years, LCMs have been used in various transportation-related topics. Ettema (2010), aiming to examine the effect of telecommuting on residential choice, developed latent class discrete choice models of residential relocation probability and residential area type choice, finding two classes of telecommuters. Walker and Li (2007) used LCM to examine the impact of lifestyle preferences on residential location behavior, concluding that lifestyle preferences affect residential choice. Tawfik and Rakha (2013) developed a latent class route choice model, assuming that drivers belong to different classes based on their aggressiveness in terms of route choice. LCMs have also been used for analyzing car ownership (Anowar et al., 2013) and the duration of social activities (van de Berg et al., 2011). However, to our knowledge, no LCMs have been developed to uncover the discrete heterogeneity of SN usage and its effects on trip making.

## 3. MODELING FRAMEWORK

The dependent variable to be dealt with in this paper is a count of the total number of trips $T_i$, measured in a sample of $N$ individuals. That is, our data form a cross-section. We assume that there are $X_n$ independent explanatory variables that affect the number of social trips. To assess the impact of the explanatory variables on the trip making, we specify a Poisson regression model in which the intercept and the coefficients of the covariates vary across the sample according to some distribution. This unobserved mixing distribution is assumed to be discrete, which results in a finite mixture model formulation (Weder et al., 1993). The results of Laird (1978) and Heckman and Singer (1984) show that estimates of such a finite mixture model may provide good numerical approximations even if the underlying mixing distribution is continuous. Heckman and Singer (1984) state, however, that maximum likelihood theory cannot be invoked to justify the large sample properties of the estimators in such cases. Because of the assumption of a discrete mixture distribution for the intercepts and coefficients, the point masses of this distribution can be interpreted as latent classes (see Lazarsfeld and Henry, 1968; McCutcheon, 1987; Gopinath, 1995; Green & Hensher, 2003) of subjects, which differ in terms of the relationship between the explanatory variables and the rate of occurrence of trips.

LCMs are appropriate for our analysis as the hypothesis is that SN usage styles exist, that these styles are not directly observable and that they affect the number of social trips that teenagers conduct. This section describes in depth the model specification process. The LCM comprises two components: the class membership model and the class-specific model, as shown in Figure 1.

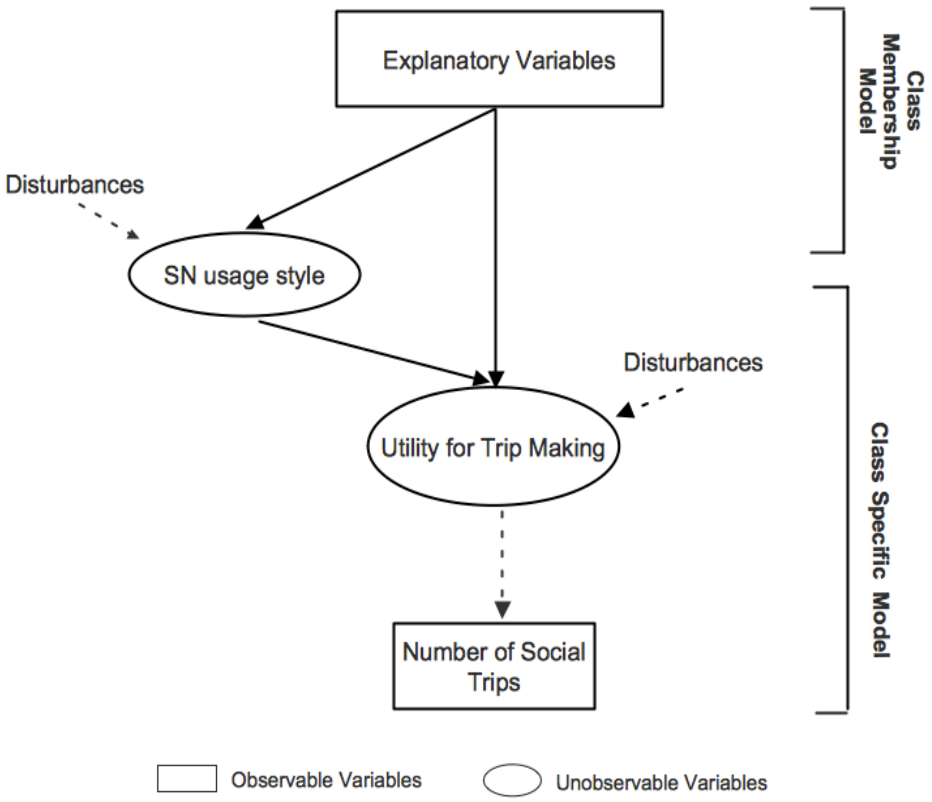


**Figure 1: Modeling Framework**

The class-specific model shows the influence of an SN usage style and socio-economic variables on the number of trips made for social purposes.

Class-Specific Model

It is assumed that each individual belongs to one and only one class, which is not known in advance. The class-specific model is a Poisson regression and represents the number of trips conducted by a latent class, varying among the latent classes. The Poisson model assumes that the number of trips any individual makes in a given time period is independent and has a constant rate of occurrence (Ben-Akiva et al., 1996). It is given by:

$$P(T_i \mid s) = \begin{cases} \dfrac{e^{-\lambda_{is}}(\lambda_{is})^{(T_i)}}{(T_i)!} & for\ \lambda_i > 0 \text{ and T=0,1,...} \\ 0, otherwise \end{cases} \qquad (1)$$

where $T_i$ is the number of trips, and $\lambda_{is}$ is the mean number of trips made by person $i$ belonging in class s.

For each class *s,* the mean number of trips for each individual $i$ is an exponential-linear function of the explanatory variables, as follows:

$$\lambda_{is} = \exp[a_s + X_{ik}\beta_{ks}] \qquad (2)$$

where $\alpha$ is the constant of class $s$, and $\beta_s$ depicts the impact of the $X_{ik}$ explanatory variables on the mean number of trips in class $s$.

The formulation of the probability density in equation (1) is conditional upon individual $i$ belonging to class $s$. Considering the observed frequencies $T_i$ as arising from a mixture of $S$ unobserved Poisson distributions (Heckman & Singer, 1984), we obtain the unconditional probability:

$$P(T_i \mid \beta_{ks}, s) = \sum_{s=1}^{S} P(T_i \mid \beta_{ks}) \quad (3)$$

which is the probability that individual $i$ conducts $T$ number of trips, conditional on the characteristics of the individual and conditional on individual $i$ being a member of class $s$.

In this way, we capture heterogeneity across individuals as: 1. a formulation is used in which the mean event rate has a discrete mixture distribution, i.e. it varies across a finite number of unobserved classes. 2. the mean trip making varies within each class, depending upon the explanatory variables.

Class Membership Model

The class membership model links the latent SN usage styles to socio-demographic variables and segments all individuals into $s_n$ classes (Swait, 1994; Hess et al., 2007; Walker & Ben-Akiva, 2011; Vij et al., 2011). While the latent class to which an individual belongs cannot be deterministically identified from the observable variables, it is presumed that the class membership probabilities can be estimated. The probability that individual $i$ has SN usage style $s$, conditional on the characteristics of that individual, $X_n$, is given by:

$$P(s \mid X_n) \quad (4)$$

LCMs simultaneously estimate class membership functions and class-specific functions. The model simultaneously breaks down teenagers' SN behaviors into classes and estimates the class-specific functions in a manner that maximizes model performance. Since the class of each individual is unknown, neither of the above equations can be estimated separately. The two components are estimated simultaneously via a LCM:

$$P(T_i \mid X_{ik,} X_{in}) = \sum_{s=1}^{S} P(T_i \mid X_{ik}, s) P(s \mid X_{in}) \quad (5)$$

where the probability of an individual $i$ making $T$ number of trips is equal to the sum over all the latent classes $s$ of the class-specific membership model conditional on class $P(T_i \mid X_{ik}, s)$ multiplied by the probability of belonging to that class, $P(s \mid X_{in})$.

Likelihood Function

In writing the likelihood function, an individual's probabilities of conducting specific numbers of trips are conditionally independent, conditioned on the individual's SN usage style (the classic latent class assumption) and on the error components. Combining the class membership model, the class-specific choice model, the error components, and the number of social trips observed for an individual, the joint likelihood function for an individual $i$ is given by:

$$L = \prod_{i=1}^{N} P(T_i \mid X_k, s) \sum_{s=1}^{S} P(s \mid X_n) \quad (6)$$

Defining the number of latent classes

One of the limitations of latent class choice models is that the researcher has to decide on the number of latent classes to use. The model cannot determine this automatically. This limitation is addressed by systematically estimating LCMs based on different numbers of classes and then choosing the model that performs best. To determine the final model specification, we estimated numerous models. The first model was a single-class model (i.e. one class where all behavior is homogeneous; this served as an overall point of reference). The second model had two classes, the third had three, the fourth had four classes and the fifth had five classes.

This approach requires a performance statistic that penalizes decreased model parsimony. To compare the estimated models and their goodness of fit, we used the log-likelihood, the corresponding values for the Rho-bar-squared, the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). Rho-bar-squared indicates how well the model predicts class memberships. AIC and BIC differ from one another according to how much weight is applied to penalize for each additional model parameter.

The $\bar{\rho}^2$ is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{L^* - k}{L^0} \quad (7)$$

The AIC is given by:

$$AIC = -2\ln L^* + 2k \quad (8)$$

The BIC imposes an additional penalty on the log-likelihood as compared to the AIC, and therefore tends to favor more parsimonious models. The equation for the BIC is:

$$BIC = -2L^{*} + \ln(N)k \quad (9)$$

where
$k$ denotes the number of estimated parameters;
$L^{0}$ is the initial log-likelihood (the log-prior) for the estimated parameters;
$L^{*}$ is the log-likelihood calculated at the values of the fitted parameters (log-posterior);
$N$ is the number of respondents.

The lower the values of BIC and AIC criteria, the better the model fits that number of classes. However, these criteria also fail some of the regularity conditions for a valid test under the null (Leroux, 1992). Asymptotically, the AIC is reported to be biased towards overestimating the number of preference classes, while the BIC is not, although for small sample sizes the BIC tends to favor too few classes (McLachlan & Peel, 2000). The BIC is often used with LCMs because it imposes a harsher penalty on the number of parameters than either the AIC or the log-likelihood value.

## 4. DATA SET AND SAMPLE CHARACTERISTICS

A web questionnaire that refers only to teenagers was designed specifically for the needs of our research. Traffic engineers and psychologists cooperated in designing the questionnaire with the aim of capturing the fundamentals of travel behavioral processes (for more details about the questionnaire, see Kamargianni & Polydoropoulou, 2013). In 2012, in cooperation with MOEC, the questionnaire was forwarded to all Cypriot high schools. The students filled in the web questionnaire during informatics lessons, under the supervision of their teachers who had received extra guidance to assist with any questions. For this paper, the sample consists of 9,714 teenagers, covering 20% of the total high school population of the country. The survey provides data on 21,060 social trips recorded over two days: 5,367 trips made on a schoolday and 15,693 trips made on a Saturday. In this paper we will focus only on the social trips that conducted on Saturday.

Table 1 presents the descriptive statistics of the sample. 55% are female and 41% are between 12 and 14 years old. 95% of the teenagers have a mobile phone, and 56% of them use their mobile phones to connect to the internet. Understanding an individual's technological environment is a vital clue in understanding how that person uses the internet, connects with others and accesses information. The average teenager owns 2.9 gadgets out of the four we asked about in our survey: cell phones (conventional or 3G/smartphones), computers (desktops and laptops), game consoles and portable gaming devices. All these gadgets increase teenagers virtual connectivity as they provide internet access. Laptops have overtaken desktops as the most commonly owned computers. Teens are enthusiastic consumers of gaming devices, both wired and portable. In total, 80% of the teens in our sample have a game console such as a PlayStation, an Xbox or a Wii, while 59% own a portable game device such as a PSP or a Nintendo 3DS. Nowadays, game devices and consoles provide new ways for teens to go online. Also, the survey indicates that the prevalent purpose for which teenagers use SN sites is for communicating with their friends. 9% of the participants indicated that they use SN mainly for playing interactive games, while 5% for being up-date for various events and their friends activities.

**Table 1: Sample descriptive statistics**

| | | Total Sample (N.Obs.=9,714) |
|---|---|---|
| Gender | Male | 45% |
| | Female | 55% |
| High School | Gymnasium (12-14 years old) | 40% |
| | Lyceum (15-18 years old) | 60% |
| Grades | Low (<14/20) | 12% |
| | Medium (14-18/20) | 46% |
| | High (18-20/20) | 42% |
| Own a mobile phone | | 96% |
| Connect to internet via mobile | | 52% |
| Mobile contract (vs. top up) | | 42% |
| Own a game console (PS, Xbox, Wii etc.) | | 79% |
| Own a portable gaming device (PSP, Nintendo 3DS) | | 50% |
| Own a desktop | | 51% |
| Own a laptop | | 82% |
| Own a tablet | | 65% |
| Time spent on SN (hours per day) | | 1.7 |
| Internet use on the schoolday (hours) | | 1.9 |
| Internet use on the Saturday (hours) | | 2.9 |
| Household size | | 4.8 |
| Siblings | | 2 |
| Household car ownership | | 2.7 |
| Household motorcycle ownership | | 0.4 |
| Family's monthly income | Low (less than 2000 Euro) | 16% |
| | Medium (2001-4000 Euro) | 27% |
| | High (more than 4000 Euro) | 35% |
| | N/A | 22% |
| Number of social trips - schoolday | | 0.5 |
| Number of social trips – Saturday | | 1.6 |
| Number of social trips - Total | | 2.1 |

## 5. MODEL ESTIMATION RESULTS

This section presents the process of defining the latent classes and the results of the model estimation. The latent class Poisson regression model described in this paper was estimated using Latent GOLD 4.5 by Statistical Innovations Inc.

The sample used for the models estimation consists of 9,714 teenagers. In the model estimation no restrictions are imposed, since all the participant teenagers are familiar and aware of social media and have internet access. Furthermore, all the data were collected in February 2012 so there is no need to impose seasonality variables in order to capture differences in trip making behavior.

### 5.1 Defining the Number of Classes

In this subsection, we briefly summarize and present the key results for the process of defining the number of classes. A number of different model specifications with different number of classes and explanatory variables were tested. We also estimated the three-, four- and five-classess models with predefined classes. To determine the optimal number of latent classes for the model, the Rho-bar-squared, BIC and AIC values of models with various numbers of latent classes were estimated and the key results are presented in Table 2.

**Table 2: Summary statistics of models with different numbers of latent classes**

| Model | | Number of Parameters | LL | AIC | BIC | Rho-bar-squared |
|---|---|---|---|---|---|---|
| 1. | Model without segmentation | 14 | -15952.13 | 31932 | 32033 | 0.0363 |
| 2. | Model with two latent classes | 40 | -15606.83 | 31293 | 31581 | 0.3052 |
| 3. | Model with three latent classes | 66 | -15417.48 | 30966 | 31442 | 0.2233 |
| 4. | Model with three classes (one class predefined) | 66 | -16214.71 | 32561 | 33036 | 0.2390 |
| 5. | Model with four latent classes | 92 | -15216.73 | 30617 | **31276** | 0.3068 |
| 6. | Model with four classes (one class predefined) | 92 | -16058.28 | 32300 | 32963 | **0.3255** |
| 7. | Model with five latent classes | 118 | -15095.46 | **30426** | 31280 | 0.2380 |

1. *Model without Segmentation:* This model is based on the assumption that all teenagers' behavior is homogeneous, forming a simple latent class. The probability that a teenager $i$ makes $T$ number of trips is based on a single Poison regression model. The Rho-bar-squared is too low and AIC and BIC values are the highest comparing to the other models.
2. *Model with Two Latent Classes:* This model is based on the assumption that there are two different SN behaviors, thus two classes. A Poisson regression model is being estimated for each class. Rho-bar-squared is improved compared to the model without segmentation; AIC and BIC values have been decreased compared to the model without segmentation.
3. *Model with Three Latent Classes:* This model is based on the assumption that there are three different SN behaviors, so three classes. The value of the Rho-bar-squared has decreased, while the BIC and AIC have been improved.
4. *Model with Three Latent Classes (one predefined*): After estimating the three latent classes model and examining the results, we decided to predefine a class as clearly indicated those who do not have an account on SN. Compared to the previous models the Rho-bar-squared has been improved, whilst the BIC and AIC have increased.
5. *Model with Four Latent Classes:* This model is based on the assumption that there are four different SN usage behaviors, so four latent SN usage classes. The value of the Rho-bar-squared is the second highest, while the BIC value is the lowest among the models.
6. *Model with Four Latent Classes (one predefined):* Following the estimation of the aforementioned model, we predefined a class representing those who do not have an SN account. The Rho-bar-squared has the highest value among all the estimated models.
7. *Model with Five Latent Classes:* We estimated this model based on the assumption that there are five different SN usage behaviors, thus five Poisson regression models are estimated; one for each class. The Rho-bar-squared has been dropped compared to the fourth model, whereas this model has the highest AIC.

All the statistics presented in Table 2 indicate that a model with SN usage segmentation is preferred over one without. The BIC suggests that the model with four latent classes is superior; the AIC indicates the model with five latent classes, while the Rho-bar-squared suggests the model with four latent classes, one of which was predefined. Although these statistics provide a lot of information each one indicates a different model. Thus, we examine further the estimation results of each model aiming to identify the model that provides the most satisfactory behavioral interpretation regarding the SN usage latent classes and trip making behavior (logical signs and interpretability of classes). Although Model 7 has the lowest AIC value, it is rejected because the behavioral differences among the classes are not clear and the classes are difficult to interpret. In terms of comparing Model 5 and Model 6, the first one has the lowest BIC value, while the other one the highest Rho-bar-Squared. We prefer Model 6 to Model 5, as availability constraints were imposed in the predefined class of the model thus improved further the behavioral interpretation. Therefore, Model 6 delivered the best and most interpretable results and was chosen to be presented thoroughly below.

### 5.2 Model Estimation Results of Latent Class Model with 4-Classes

The latent class Poisson regression model estimation results consist of parameter estimates for the class-membership models (Tables 3) and the class specific model (Table 5). All of the parameters in these tables resulted from simultaneous estimations of the class-specific Poisson regression and class membership model.

#### 5.2.1 Estimation results for the class-membership model

Table 3 provides the parameter estimates of the class-membership models that help us to identify the predictors of the latent SN usage styles. Class membership model is a multinomial logit model (MNL) of the probability with which each teenager belongs to one and only one of the three latent classes. Class 1 represents the 43% of the total sample, Class 2 the 25% of the sample, Class 3 the 22% of the sample and Class 4 the 10% of the sample.

Variables regarding time allocation on SN can be seen to exert a significant effect on SN styles. In Class 1 the variable regarding time allocation that is most significant is "Allocate 1 to 2 hours on SN" having a positive effect on this class. Owning 2 to 3 out of the 4 gadgets that we asked in the survey has also a positive effect, while high gadget ownership has a negative sign and it is statistically insignificant. Connecting to the internet via mobile phone and having a mobile contract affect positively the probability of being in this class. Having an account on more than 3 SN affects the probability of belonging to this class as well. Regarding Class 2, teenagers who do not allocate time to SN daily are more likely to belong to this class. Owning only one gadget and more specific owning only mobile phone has also a positive affect and it is statistically significant for Class 2. Regarding Class 3, spending more than 4 hours per day on SN affects positively the probability of belonging in this class, while the three most statistically significant variables are owning 4 gadgets, having an account on more than 3 SN and going to internet cafe at least once per week. Class 4 is predefined representing those who do not have an SN account and as a result restrictions to variables regarding time spent on SN are imposed.

In Table 3 are also given the Wald statistic results. For each set of parameter estimates, the Wald statistic considers the subset associated with each class and tests the restriction that each parameter in that subset equals the corresponding parameter in the subsets associated with each of the other classes. That is, the Wald statistic tests the equality of each set of regression effects across classes. Wald statistic results indicate that the parameters used for the class specific model vary significantly at 95% level of confidence indicating significant heterogeneity across the classes.

**Table 3: Estimation results for the class-membership model**

| | Class1 | | Class2 | | Class3 | | Class4 | | Wald statistic |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | |
| α | 2.11 | 5.60 | 1.87 | 5.61 | -0.33 | -1.57 | -4.32 | -7.09 | 71.15 |
| Allocate no time on SN daily | -1.26 | -2.40 | 6.03 | -1.90 | -1.38 | -2.76 | - | - | 141.76 |
| Allocate more than 4hours daily | -1.13 | -4.46 | -0.78 | -3.17 | 3.67 | 4.30 | - | - | 38.89 |
| Allocate 1 to 2 hours daily | 4.42 | 7.25 | -0.25 | -4.62 | -0.69 | -2.15 | - | - | 29.73 |
| Own 4/4 gadgets (mobile phone, tablet, game consoles, portable game device) | -1.16 | -1.80 | -0.89 | -1.99 | 2.36 | 7.58 | -2.12 | -2.61 | 43.51 |
| Own tablets, 3G phones (2-3/4) | 2.12 | 5.87 | -0.13 | -1.32 | -0.90 | -2.53 | -0.53 | -4.27 | 30.02 |
| Own 1/4 gadgets (conventional mobile phones) | -0.48 | -4.15 | 1.66 | 10.7 | -0.57 | 3.84 | 2.32 | 6.08 | 103.80 |
| Mobile contract (v. top up/ no contract) | 1.47 | 3.21 | -0.92 | -2.43 | 2.12 | 4.21 | -1.23 | -2.76 | 82.17 |
| Connect to internet via mobile | 0.97 | 2.15 | -0.71 | -2.59 | 0.76 | 5.92 | -0.99 | -5.26 | 67.70 |
| Going to internet cafe at least once per week | -0.32 | -1.83 | -1.49 | -5.18 | 1.62 | 6.74 | -0.85 | 4.12 | 29.45 |
| Have an account on more than 3 SN | 0.44 | 3.09 | -1.35 | -3.61 | 2.39 | 6.90 | - | - | 26.95 |
| Have an account on 1 SN | 1.78 | 6.29 | 1.51 | 2.50 | -1.30 | -5.47 | - | - | 40.32 |

In order to make more clear which are the predominant characteristics of each class and in doing so to name the classes, we rated the variables of each class of the class membership model based on their importance. This process is determined by taking the difference between the highest and lowest value of each variable as observed in the survey and multiplying this difference by the coefficient of the variable (see Walker & Li, 2007). The absolute value of this product gives the order of potential impact on the utility.

**Table 4: The most important values for each class**

| | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|
| | *Rational SN usage* | *Indifferent to SN usage* | *SN addicted* | *Non SN users* |
| 1 | Allocate 1 to 2 hours daily | Allocate no time on SN daily | Allocate >4hours daily | Own 1/4 gadgets |
| 2 | Own 2-3/4 gadgets | Own 1/4 gadgets | Have an account on >3 SN | Connect to internet via mobile |
| 3 | Have an account on 1 SN | Have an account on 1 SN | Own 4/4 gadgets | Mobile contract |
| 4 | Allocate no time on SN daily | Mobile contract | Mobile contract | Going to internet cafe |
| 5 | Own 4/4 gadgets | Going to internet cafe | Going to internet cafe | Own 2-3/4 gadgets |
| 6 | Allocate > 4hours daily | Have an account on >3 SN | Have an account on 1 SN | Own 4/4 gadgets |
| 7 | Connect to internet via mobile | Mobile contract | Allocate no time on SN daily | |
| 8 | Own 1/4 gadgets | Own 4/4 gadgets | Own 2-3/4 gadgets | |
| 9 | Have an account on >3 SN | Allocate >4hours daily | Connect to internet via mobile | |
| 10 | Going to internet cafe | Connect to internet via mobile | Allocate 1 to 2 hours daily | |

Members of latent Class 1 (Rational SN usage) are more likely to spend 1 to 2 hours on a daily basis on SN and own 2 to 3 out of 4 gadgets. Based on the literature review of other social surveys on teenagers SN usage behavior, we conclude that this is a rational amount of time, since the average time that the majority of the current teenagers spend in a typical day on SN is 1.5 hours (Teen Facebook Statistics, 2012). Moreover, these teenagers have an account on one SN and they connect on their SN account via their mobile phones. The prevalent gadgets that they use are 3G phones or smartphones and game consoles either portable or not.

The prevalent characteristics of Class 2 indicate indifference to SN usage. Members of this group do not spend time on SN on a daily basis, whilst they have an account on 1 SN. Moreover, the members of this class own only one gadget and more specific a mobile phone usually old-fashioned (conventional).

Class 3 indicates SN usage addiction. Although we do not include psychological indicators in this paper to assess addiction, the results of this class indicate that its members spend more than 4 hours per day on SN (more than average), they have all the gadgets that we asked in our questionnaire (3G mobile phone or Smartphone, tablet, game console and portable game devices) and connect on the web via their mobile phones. In Class 4 belong those who are non-users of social media, while owning 1 out of 4 gadgets is the predominant variable in this class.

### 5.2.2 Estimation results of the class specific model

Taking into account the segmentation of the SN usage patterns, we now continue with the class specific model to check whether the SN usage styles and the available socio-economic characteristics are good predictors of the trip making behavior. The estimation results for the class specific model are shown in Table 5. The explanatory variables include characteristics related to gender, age, internet access at home, number of devices with internet access in household interacted with the number of household size, monthly family income, household car ownership, parents' educational level, residential area characteristic. All of the variables used in the class specific model are statistically significant at the 95% and have significantly different effects across classes at the 95% confidence level.

**Table 5: Estimation results for the class-specific model**

| | **Class1** *Rational SN usage* | | **Class2** *Indifferent to SN usage* | | **Class3** *SN addicted* | | **Class 4** *Non SN users* | | Wald statistic |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | |
| Intercept | 1.43 | 4.92 | -0.88 | -2.98 | 1.12 | 3.49 | -0.65 | -2.37 | 46.88 |
| Female | 0.32 | 9.18 | 0.13 | 3.72 | -0.95 | -8.82 | 0.21 | 3.47 | 113.68 |
| 14 to 18 years old (vs. 12-13) | 0.23 | 4.04 | -0.40 | -6.01 | 0.58 | 2.57 | -0.18 | -2.09 | 50.55 |
| Low family income | 0.26 | 2.77 | -1.10 | -10.90 | 0.35 | 3.08 | -0.41 | -4.90 | 93.20 |
| Medium family income | 0.61 | 1.98 | 0.17 | 3.87 | -0.44 | -2.89 | 0.35 | 3.31 | 62.57 |
| High family income | 0.26 | 3.91 | -0.13 | -1.98 | -1.61 | -3.61 | -0.72 | -7.26 | 73.39 |
| Household car ownership (continuous) | 0.28 | 2.10 | 0.48 | 2.92 | 0.22 | 6.39 | 0.13 | 1.97 | 30.03 |
| Available internet access at home | 0.18 | 3.93 | -0.93 | -5.56 | -0.38 | -7.73 | -0.27 | 2.31 | 97.61 |
| Number of available gadgets with internet access in household divided by the number of household members | 0.20 | 5.00 | -0.15 | -2.40 | 1.01 | 3.04 | -0.26 | 1.67 | 32.50 |
| Urban (vs. suburban) | 0.19 | 3.53 | 0.36 | 2.83 | -0.96 | -5.45 | -0.71 | -2.24 | 24.32 |
| Father-Low Educational level | 0.51 | 1.96 | -0.15 | -3.19 | 0.35 | 3.12 | 0.21 | 2.61 | 35.45 |
| Father-High Educational level | -0.31 | -1.97 | 0.92 | 2.03 | 0.45 | 3.50 | -0.19 | -1.98 | 12.60 |
| Mother-Low Educational level | -0.37 | -1.98 | 0.28 | 2.22 | 0.43 | 4.17 | 0.51 | 7.14 | 81.36 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Mother-High Educational level | 0.19 | 2.15 | -0.28 | -2.72 | -0.13 | -2.27 | -0.13 | -2.51 | 18.89 |

The results of the class-specific model indicate that the rational SN usage style (Class 1) increases/stimulates the number of social trips having at the same time the strongest effect among the intercepts of the other three classes. SN addiction (Class 3) also increases/stimulates the number of social trips, while the indifference to SN (Class 2) and non-SN-users (Class 4) decrease/ substitute for the number of social trips. The mean number of social trips conducted in a typical Saturday is 1.9 for the Class 1; 1.2 for Class 2; 2.2 for Class 3; and 1.0 for Class 4.

Demographic dummy variables are also used in order to explain the dependent variable. Females (girls) are more likely to belong in Class 1 and boys in Class 3 affecting negatively the number of social trips. Younger teenagers aged between 12 to 13 years old are more possible to categorized as rational SN users having a negative sign indicating that contact less social trips. Older teenagers aged between 14 to 18 years old are more likely to belong to rational and addicted SN usage styles, while through a positive sign age strongly affects the number of social trips. All the three levels of income (the base level for this variable is Income N/A) in Class 1 affect positively the number of social trips. In Class 2 low and high family income decreases the number of trips, while medium family income increases the probability of trip making for social purposes. Participants with high family income are less likely to be non SN users (Class 4). Regarding households' car ownership, as the number of cars available in household increases, the probability of social trip making increases across all the four classes. For rational and addicted SN users, as the ratio of available gadgets with internet access in household divided by the number of household size increases, the probability of making social trips increases too. Regarding the other two classes, as this ratio increases the possibility of conducting social trips decreases. Parents' level of education affects in different ways the dependent variable across the classes. Fathers' low educational level decreases the possibility of conducting social trips in Class 2, while increases this possibility in Class 1, 3 and 4. Higher educational level of father significantly affects the dependent variable in Class 2 and 3. Mother's higher level of education affects significantly and in a positive way the dependent variable in Class 1.

## 6. CONCLUSIONS

Having in mind that current teenagers have grown up in a completely different environment regarding internet and social media availability than in that the current middle-aged persons have grown up, we strongly believe that it is worthwhile to clarify for the teenagers' travel behavior as a generational gap is created. Investigation of teenagers' behavior could provide significant insights about the trends of this generation to policy-makers and in doing so to develop the future transportation policies.

This paper has explored the influence of various social networking (SN) usage styles on adolescents' travel behavior. The specific aim was to find out if SN usage substitutes for or stimulates teenagers' trip making behavior. At the same time, we postulated that SN usage is not unique across the sample and that SN usage styles exist and affect the trip making behavior in different ways. In doing so, we built a behavioral framework that captures the influence exerted by SN usage styles on teenagers' social trips. Next, we develop a Latent Class Poisson Regression model consisting of two parts: 1. the class membership model, which links the latent SN usage styles to socio-demographic variables; and 2. the class-specific choice model, which is a Poisson regression and shows the influence of an SN usage style and socio-economic variables on the number of trips made for social purposes. The methodology is tested with data from a large-scale transportation survey that we launched in Cyprus in co-operation with the MOEC in 2012. The participants cover the 20% of the total high-school population (aged from 12 to 18 years old), a fact that allow us to estimate accurate models reflecting the behavior of all the teenagers in the country.

The class membership model suggests that teenagers cannot be treated as one uniform group regarding the SN usage but instead shows considerable heterogeneity. After the estimation of models with various latent classes and the assessment of their goodness-of-fit, we concluded that four latent SN usage styles/classes exist. Class 1 includes those teenagers who use SN in a rational way. Members of Class 2 show indifference in SN usage. Members that belong to Class 3 are highly SN oriented or in simple words SN addicted. Teenagers who do not have an account on social media comprise Class 4.

The results of the class specific model assist us to respond to our question regarding the effect of SN usage on trip making behavior. The answer is that those teenagers who use SN rationally and those who are addicted to SN are more possible to conduct more trips, thus SN usage stimulates the number of trips made for social purposes. On the other hand, SN indifference and no usage substitute for the social trips that teenagers conduct. The results make clear that in order to understand the impact of SN usage on trip making behavior, it is important to distinguish different types of SN users. The approach taken here, by requiring less complicated econometrics, should remain within reach of many more practitioners with standard training in maximum likelihood estimation, and still deliver more plausible and substantively different estimates than when segmentation is ignored.

Regarding transport planners and policy makers, they should strongly take into account that the expansion of SN sites generally stimulates the number of social trips that teenagers conduct, a behavior that could be maintained in their adulthood as well. These trends could shake some transportation policies created under the assumption that generally ICT usage substitutes for trip making.

This research also provides insights into the rapidly growing literature investigating the relationship between ICT and travel behavior. Moreover, the innovative data collection and methodology used here could be of high importance to researchers dealing with this age group.

Concluding, this paper is a first attempt to investigate SN usage styles and it will be extended in several directions in the future. Further work includes the incorporation of psychometric (attitudinal and perceptional) indicators regarding the SN usage and scale parameters (adjusted scale LC) for capturing the uncertainty in each class. This will lead to the estimation of more advanced LCM providing a richer and more powerful explanatory ability.

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