Social influence and impact of social media on users' mobility decisions

Maria Karatsoli [ID], Eftihia Nathanail [ID]

Department of Civil Engineering, University of Thessaly, Volos, 38334 Greece
makarats@uth.gr

Abstract: Social media are deemed influential in making decisions and seeking advice. Due to their explosive growth as critical channels for information, their content can trigger a place visit, a change of transport mode or destination, or plans' cancellation. The main objective of this paper is to investigate the influence of social media on users' activity and mobility planning. Responses of 738 participants in a digital survey were used to formulate ordinal regression models. The developed models determine the contribution of users' demographic characteristics, travel characteristics and social media usage to mobility decisions after using social media as a source of information. These decisions were expressed in two dependent variables; (i) the impact of social media use in activity and mobility planning; (ii) the impact of the proposed transport mode by social media information, on mode choice. Analysis of the results indicated that the models, which considered all the characteristics together, could better predict the two variables.

Keywords: activity planning, mode choice, questionnaire survey, travel behavior, sustainable mobility, Information Communication Technology, ordinal regression.

1. Introduction

Social influence exists widely in an individual's behavior. Social interaction and imitation have an impact on peoples' decision behavior. Disciplines such as sociology, psychology and economics have analyzed extensively the social influence (Axsen & Kurani, 2012; Axsen & Kurani, 2014). Travel and traffic associated behaviors are also affected by social influence factors (Zhang et al., 2019).

Social media began their operation as basic platforms where people could share posts, videos and photos with their web friends and broaden their social connections. Over the years, social media have undergone a growth that led to a high impact on users' final decisions regarding an activity, mobility or products' purchase (Yamagishi, et al., 2016). The increasing time being spent on social media, the instantaneous and real-time access to tips and guides, traveling instructions, offers and discounts or inspirational photos/videos have changed the way users plan an activity (Abbasi, et al., 2015). The shared content is a valuable source of information that can be easily accessible at low cost, thus often affects users' perceptions and choices regarding activity planning and mobility. By combining data, from

text and videos to geographical information, social media can play a decisive role in motivating, empowering and engaging users.

Transport related content on social media allows the comparison of travel patterns and affects identity formation and travel choices. According to Yoo and Gretzel (Yoo & Gretzel, 2011), social media are an important source of information for travelers, the majority of whom trust their content. Other studies showed that when users acknowledge a high value to social media, it results positively in the social media usage for travel information searches (Ching & Koo, 2015) and it increases the possibility of canceling their trip, based on social media information (Milioti, et al., 2019).

The users' profiles are the main constructs that affect the social media usage for travel planning and influence their final decision. Using an online survey on travelers, the study of Ayeh et al. (2013) investigated the factors that affect their intentions to use social media for specific purpose of travel planning and reported that mostly young people use social media to plan their trips. Simms et al. (2012) reported that demographic characteristics such as age, levels of income and ethnicity affect social media usage for travel planning. The findings showed that younger users and users with higher levels of income are more likely to turn to social media content for travel planning. Holding a driver's license, being a frequent public transport user or using mainly a non-sustainable mode for daily commuting are factors that influence commuters' final decision (2000). Also, those who travel frequently use social media to get information during their trip more often than those who travel less, according to Schroeder and Penninghton-Gray (2014), who investigated the role of social media use in the different phases of travel decision-making.

However, an investigation and comparative analysis of how the impact of social media on activity and mobility planning is affected by different characteristics, such as demographic, travel and social media related data, has not been attempted. Furthermore, the contribution of social media towards sustainable traveling has not been particularly addressed based on different characteristics of a user. Aiming at covering these gaps, the present work explores the impact of social media on users' activity and mobility plans, as affected by their demographic profile, travel behavior and social media usage. Moreover, it focuses on the identification of the role of social media information in the users' selection of transportation mode. Therefore, compared with the existing studies, this paper contributes to urban mobility research through the identification of demographic, travel and social media usage characteristics that contribute to users' final decisions as affected by social media information. The remaining text is structured in three more sections. The second section gives an overview of the contribution of information and communication technologies (ICT) and social media in people's decisions regarding their activity and mobility planning, their usage in information dissemination, and facilitation in data collection about mobility patterns and traffic dynamics. The methodology followed, in this work, for collecting the data and identifying the constructs of social media impact on activity and mobility planning and decision making is explained in the third section. The fourth section presents the results of the survey conducted in a sample of 888 social media users and develops relational models to investigate the contribution of users' demographic characteristics, travel preferences and social media usage to the impact of social media use on activity and mobility plans, and on the final choice of transportation mode for their trip. The conclusions and limitations of the study are discussed in the last section of the paper.

2. Literature review

The uptake of ICT has increased rapidly and changed the way that people plan their activities and mobility. Recent ICT innovations have a positive impact on sustainability, as they resulted in increased interest in sustainable forms of mobility.

Studies have documented that ICT has a significant influence on transport behavior. ICT provides access to travel information, transport modes comparison, work from home, online payments, travel planning tools (2017). Thus, it is considered an important added value to transport systems. Line et al. (2011) found that there is a cumulative impact of ICT on users' daily lives. The findings were based on a qualitative diary and an interview of students between 18-28 years old and part-time working mums. Cohen-Blankshtain and Rotem-Mindali (2016) examined the integration of ICT with Intelligent Transport Systems (ITS) and assessed its impact on travel demand, urban form and urban mobility. A thorough review was done, concluding that ICT have changed the perceptions of distance, accessibility,

and availability. The authors noted that the ICT innovations lead to travel substitution since substitution of physical by virtual presence has grown. ICT-based activities could lead to a reduction in average time and less interest in private car ownership (Delbosc & Currie, 2014; van Wee, 2015; Belgiawan, et al., 2014).

The growth of ICT, through online platforms, smartphone applications and social media plays an important role in transport contexts by facilitating travel and allowing virtual presence (Germann, 2012). A mobile phone or any device connected to Internet has the potential to bring a significant change in the way people move by providing real-time information about traffic and travel times, appropriate transport modes, shortest routes, and so on. This information can affect people's mobility behavior since it allows better planning of their activities and mobility. The ubiquitous mobile technology and web-based applications enabled the emergence of social media.

In 2010, Xiang and Gretzel confirmed the importance of social media in seeking travel information. Their analysis showed that social media constitute a substantial part of the search results, indicating that search engines likely direct travelers to social media sites. In a following research, Yoo and Gretzel (2012), argued that social media have a significant impact on travel planning and decision-making, first in terms of accommodation and facilities, and then in terms of activity type and location. In the study of Gössling and Stavrinidi (2015) Facebook profiles were analyzed to investigate the presence of mobility aspects on social media, discussing also how individual's mobilities can set in motion competitive travel. A qualitative exploratory research approach was chosen to determine inter-relational dynamics between corporeal and imaginative travel and their importance for society. The study used ethnographic content analysis (ECA) to structure and evaluate shared content on 50 Facebook profiles. Results showed that Facebook increases sociality and facilitates mobility through advice and invitations.

Keith et al. (2012) developed a formal model of spatial technology diffusion to capture the information flow through people's social networks. The authors investigated to what extend spatial clustering in social networks could explain observed clusters in adoption patterns of hybrid-electric vehicle ownership. Goetzke and Rave (2012) used a binary discrete choice framework to investigate the factors that affect bicycle use in Germany. The analysis showed that social network effects increase bicycle use for shopping and recreational trip purposes, but not for working or educational purposes. Zhang et al. (2019) studied the route choice behavior in a two-route network under social influence. The effects of social learning on participant's route choice were studied by proposing an instance-based learning theory (IBLT) model with social learning. As an extension of the study, it was shown that the more participants choose the recommended routes, the better the traffic conditions. Social influence has also an impact on driving behavior. A driving simulator study tested the impact of passenger presence who applied peer influence on driving behavior of male teenagers. The findings support the contention that social influence has an impact on driving risk behavior and are in line with social norms theory (Bingham, et al., 2016).

Social networking is characterized by interactivity and encourages users to share opinions, photos, experiences and locations with their web friends. This content builds awareness and shapes users' activity and mobility preferences (Mohammadreza, 2012). The instantaneous and real-time access to relevant tips and guides, travelling instructions, specific offers and discounts or inspirational photos/videos has ultimately changed the way users plan an activity (Esztergár-Kiss & Tettamanti, 2019).Transit agencies use social media to connect with commuters since the online platforms can be a powerful tool for engaging and communicating with the public. Cottril et al. (2017) evaluated a social media strategy for the dissemination of transport information during a large event. The coordination of the multiple services and information providers for the dissemination of a reliable message and the public response to it was also examined. The findings of this survey demonstrated the benefits of social media as a medium for sharing accurate and trusted information.

Most of the studies that are related to urban mobility (Fu et al., 2015; Byon et al., 2009; Hasan et al., 2013; Lee et al., 2017) explore the use of social media data to collect travel information and attributes (i.e. transport mode, activity patterns, traffic incidents). Several studies have shown attention to extract information from social media to track and analyze human mobility. Information about trip purpose, transport mode, location data, activity duration and sociodemographic characteristics can be obtained directly and at low cost from social media. The study of Manca et al. (Manca et al., 2017) explored the way that social media data can be used to infer knowledge about urban dynamics and mobility patterns in an urban area. A workflow that shows how social media can become a source to reveal these patterns

was identified, and then applied into a real case study. Tasse and Hong (2018) presented ways of using geotagged social media data to develop an understanding of urban areas, categorizing the opportunities for a city planner, small business owners and individuals. Lee et al. (2016) used geotagged Twitter data from the greater area of Los Angeles. A Twitter-based Origin-Destination (OD) matrix was compared with a recent OD matrix provided from the 4-step model output. Regression models were estimated to measure the correlations between the two OD data. The results showed that location-based social media data on large scales have an added value on travel demand modeling. Hassan and Ukkusuri (2015) used Foursquare check-ins in New York City. The study aimed to infer individual lifestyle behavior based on activity-location choices in social media.

Data from social media have been utilized to extract information about traffic conditions for network management purposes. Real-time information about incidents, schedules, fares and projects are some examples of how transport companies use social media (Bregman, 2012). Tian et al. (2016) verified traffic incidents that were posted on social media by comparing them with field data from installed cameras. The results showed that users' tweets about true and severe incidents were shared more often compared to false and minor incidents. Gao et al. (2012) investigated how social media can enhance transportation management. The pattern of users' Foursquare check-ins was used to study the social-historical ties on location-based social networks. In the study of Fu et al. (2015) an approach has been developed for the extraction and analysis of real-time traffic-related data from Twitter. The preliminary results showed that social media can be used as a supplementary source for traffic incident data collection.

3. Methodology

3.1. Data collection

The present research attempted to explore the impact of social media use on activity and mobility planning and on mode choice. Data were collected through an online questionnaire entitled "Investigating the role and potential impact of social media on mobility behavior". The survey was built on SurveyMonkey and lasted one year, from January 2018 to January 2019. The survey link was mainly disseminated via the social media Facebook, Instagram and LinkedIn of the authors and via email to the contact list of Traffic Transportation and Logistics (TTLog) laboratory, consisting of 3436 recipients.

The questionnaire consisted of three parts. The first part collected information about the demographic and travel characteristics of the respondents, the second part recorded the social media usage and the last part asked about the impact of social media on activity and mobility planning and mode choice. Demographics included gender, age groups, occupation and country of residence. In particular, for the latter, owing to the nationality of the researchers, an identifier was used for separating Greece from other countries. For the travel characteristics, respondents were asked if they hold a driver's license and if they mainly use a sustainable or a non-sustainable transport mode for their activities. The category of sustainable mode users includes the participants that use only sustainable modes for their daily commute (public transport, biking or walking), while the category of non-sustainable mode users includes participants that use at least one non-sustainable mode of transport for their mobility (car or motorbike). The frequency of public transport use was reported on a 5- point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5). For the social media usage, respondents stated the number of days per week they use social media, the average minutes spending when using a social platform and the time of the day that they use more frequently social media. They were also asked whether they use a supplementary source, except for social media to facilitate them for the mobility/activity planning. Then, the respondents answered if they believe that social media help them with their mobility decisions. Finally, in the last part, respondents were asked if social media affects their activity and mobility planning, and if advice from social media about transportation modes affects their mode choice. All these last questions were rated using the 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5).

3.2. Applied methods

A first analysis of the data was done through descriptive statistics. Sample characteristics, frequency distributions per characteristic, mean values and standard deviations (SD) were calculated, where applicable. Then, ordinal regression analysis was conducted to analyze the influence of social media use in activity and mobility planning and mode choice, as affected by explanatory variables associated with demographic information (Simms, 2012), travel characteristics (Gunnarsson, 2000) and social media usage (Chung & Koo, 2015; Milioti, et al., 2019) that contribute to users' final decisions after social media use. Preliminary analysis was done to identify the independent variables that were not highly correlated with each other, to be used in the same model. The ordinal regression approach was chosen because it is more appropriate for data measured on a Likert scale compared to common statistical models which may simplify the collected data by assuming equal intervals between the scoring categories. Ordinal regression analysis, based on the cumulative-odds principle, treats the dependent variables as an ordered categorical variable (Stewart, et al., 2019; Gutierrez, et al., 2016; Osborne, 2015; Hosmer, et al., 2013). The results of ordinal regression can be easily interpreted and are straightforward regarding the occurrence probability of an event. This method was also used in several studies and aims at identifying the strength of the effect that the independent variables have on a dependent variable (D'Ambra, et al., 2020; Booth, et al., 2019; van de Berg, et al., 2017).

The selection of the link function that would be more appropriate for the model is another important decision in the formulation of the ordinal regression models. Logit, Complementary log-log, Negative log-log, Probit and Cauchit are link functions that allow the estimation of the models. The selection of the link function depends on the distribution of the dependent variable values. Logit function is applied when the values are evenly distributed. The Complementary and Negative log-log are more suitable when the higher or the lower categories of the dependent variable are more probable, respectively. The Probit link function provides better predictions of the dependent variable when the responses are normally distributed. Finally, the Cauchit link function is mainly used when the dependent variable has many extreme values (Staus, 2008).

4. Research results

The sample characteristics as well as the results of the ordinal regression analysis are presented in the following sections.

4.1. Sample characteristics and social media usage of the respondents

The total number of participants was 1073, however, the final sample size comprised 888 users, who fully completed the questionnaire. Table 1 shows the frequencies and percentages of respondents' demographic and travel characteristics. In terms of demographics, 61.1% of the participants are women, 73.3 % are between 18 and 35 years old and 51.4% have a full-time job. 70% of the respondents live in Greece and the rest 30% live in Germany (5%), the United States of America (3%), the United Kingdom, France and Italy (2% each) and other countries (16%). Regarding the travel characteristics, 71% of the participants hold a driver's license, 47% use only sustainable transport modes in their daily life, while 8.1% stated that they never use public transport.

91% of the participants responded that they use social media. The 804 participants that gave a positive response to this question were able to proceed to the next parts of the survey. The rest 9% were redirected at the end of the survey since the following sections were to be responded by social media users. According to users' statements, Facebook and Instagram are the most used social media platforms. Analytically, 90.2% stated that they use Facebook, 73.4% Instagram, 42.8% LinkedIn, 29.5% Pinterest and 22.3% Twitter. It is noted that participants could select multiple choices.

Table 1: Respondents' personal information and travel characteristics		
Personal Information	**Frequency**	**Percent (%)**
Gender		
Female	543	61.1
Male	345	38.9
Age		
<18	12	1.4
18-25	330	37.2
26-35	321	36.1
36-45	127	14.3
>46	98	11
Occupation		
Student	335	37.7
Part- time job	57	6.4
Full- time job	456	51.4
Unemployed	37	4.2
Other	3	0.3
Country of residence		
Greece	625	70.4
Other countries	263	29.6
Driver's license		
Yes	676	76.1
No	212	23.9
Transport mode users		
Sustainable transport mode users	417	47
Non- sustainable transport mode users	471	53
Public Transport use		
1-Never	72	8.1
2-Seldom	193	21.7
3-Sometimes	192	21.6
4-Often	273	30.7
5-Always	158	17.8
	Mean=3.34 , SD=1.202	

The social media usage of respondents appears in Table 2. The results show that 86.7% of the participants use social media every day, 33.6% spend 6 to 15 minutes online every time they check their social media accounts and 65.7% use more frequently social media between 17:00 and midnight. As 8.2% of social media users stated that they never use social media for their mobility/ activity planning, the last four parameters in Table 2 refer to the rest of 738 participants who use social media for their travel arrangements and activity planning. Moreover, 91.3% stated that except for social media use a supplementary source of information during the mobility/ activity planning phase. The majority of the respondents answered that social media help them with their final decision sometimes (45.7%) and often (30.1%). In particular, 46.9% of the respondents stated that social media influences their activity and mobility planning sometimes. 35.9% of the participants stated that their mode choice is influenced sometimes by social media information.

Table 2: Use of social media		
Social media usage	Frequency	Percent (%)
How many days per week do you use social media		
Everyday	697	86.7
5-6	52	6.5
4-3	24	3.0
2-1	20	2.5
More rarely	11	1.4
How many minutes do you spend on average per time		
0-5	170	21.1
6-15	270	33.6
16-30	166	20.6
31-60	82	10.2
>60	116	14.4
What time of the day do you use most frequently social media		
07:00-12:00	101	12.6
12:00-14:00	43	5.3
14:00-17:00	92	11.4
17:00-00:00	528	65.7
00:00-07:00	40	5.0
Do you use any other sources of information except for social media		
Yes	674	91.3
No	64	8.7
Do you consider that social media help you in your final decision		
Never	18	2.4
Seldom	94	12.7
Sometimes	337	45.7
Often	222	30.1
Always	67	9.1
	Mean=3.31 , SD=0.892	
Does social media use affect your activity and mobility planning		
Never	65	8.8
Seldom	236	32
Sometimes	346	46.9
Often	84	11.4
Always	7	0.9
	Mean=2.64 , SD=0.832	
Does the proposed transport mode by social media information affect your mode choice?		
Never	79	10.7
Seldom	191	25.9
Sometimes	265	35.9
Often	160	21.7
Always	43	5.8
	Mean=2.86 , SD=1.058	

4.2. Ordinal regression analysis

Ordinal regression models were applied to determine the contribution of demographic variables, travel characteristics and social media usage to mobility decisions after using social media as a source of information. These decisions were expressed in the two dependent variables ; (i) the impact of social

media use in activity and mobility planning; (ii) the impact of the proposed transport mode by social media information, on mode choice.

Two sets of four ordinal regression models were developed. For each dependent variable, the first model used as explanatory variables the demographic characteristics, the second considered the travel characteristics, the third implemented those characteristics regarding the social media usage, and the fourth comprised all variables. Table 3 includes a list of the examined variables and their abbreviations for a better understanding of the analysis. Responses of 738 participants that stated that they use social media for their activity and mobility planning, were used to formulate the models.

Table 3: Abbreviations of the examined variables	
Dependent Variables	**Abbreviation**
Impact of social media use on activity and mobility planning	ISMU
Impact of the proposed transport mode based on information provided by social media on mode choice	IPTM
Explanatory Variables	**Abbreviation**
-Demographic characteristics	
Gender	GEN
Age	AGE
Occupation	OCC
Country of residence	RES
-Travel characteristics	
Driver's license	DL
Transport mode	TM
Public transport use	PTU
-Social media usage	
Days/week of social media use	DSMU
Average minutes of social media use	MSMU
Time of the day of social media use	TSMU
A supplementary source of information	SSOI
Help of social media use on the planning phase	HOSM

4.3. Impact of social media use on activity/mobility planning

The first developed model (Model I) examines the relationship between the impact of social media use (ISMU) on activity and mobility planning and the demographic characteristics.

Model I: $(ISMU) = f(GEN, AGE, OCC, RES)$, where GEN is the gender, AGE the age of participants, OCC the occupation and RES the country of residence. The research hypothesis 1 (H1) is that the demographic characteristics are good determinants of the impact of social media use on activity/mobility planning.

The second model investigates whether travel characteristics of participants are predictors of the impact of social media use on mobility/ activity plans.

Model II: $(ISMU) = f(DL, TM, PTU)$, where DL shows if the user holds a driver's license, TM is the most preferred transport mode (sustainable or non-sustainable transport mode) and PTU depicts the use of public transport. The second research hypothesis (H2) is that the travel characteristics are good determinants of the impact of social media use on activity/mobility planning.

The third model includes as independent variables the participants' responses that are related to social media use.

Model III: $(ISMU) = f(DSMU, MSMU, TSMU, SSOI, HOSM)$, where DSMU is the days per week that a participant uses social media, MSMU the average minutes spending when using a social platform, TSMU the time of the day that a participant uses more frequently social media. SSOI is the use of a supplementary source, except for social media for better mobility/ activity planning and HOSM is related to the respondents' statement regarding the overall help of social media use on the planning phase. The third research hypothesis (H3) is that characteristics related to social media use predict the impact of social media use on activity/mobility planning.

The fourth model includes all the independent variables of the previous models.

Model IV:

$$(ISMU) = f (GEN, AGE, OCC, RES, DL, TM, PTU, DSMU, MSMU, TSMU, SSOI, HOSM)$$

The fourth research hypothesis (H4) is that the impact of social media use on activity/ mobility planning is predicted by all the characteristics.

To decide which link function gives good fits for the examined data, the distribution of values for the outcome variable was examined based on the histogram for the dependent variable. Based on (Staus, 2008) the Logit link function was selected to run the ordinal regression analysis of our models, since the middle category of the dependent variable was more probable. The higher and lower categories recorded less responses (Fig. 1).

Figure 1: Histogram of impact of social media use in activity and mobility planning
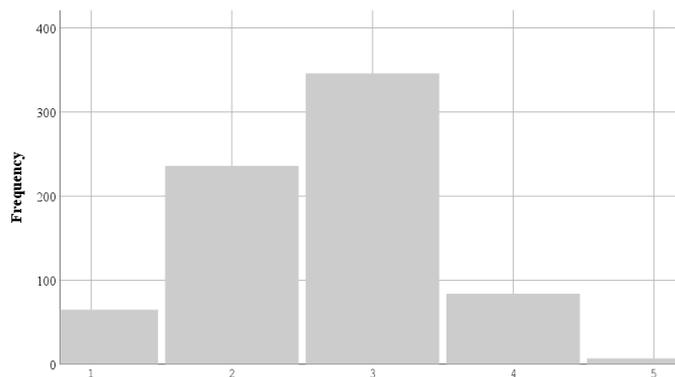
As there were cells with zero frequencies, the interpretation of fit statistics is difficult to be done and thus chi-square based fit statistics had to be evaluated very carefully.

The Model Fitting Information of the four models were examined to find out if the models give adequate predictions. The significant chi-square statistic (Sig.=0.000) indicates that Models III and IV give a significant improvement over the baseline intercept-only model. Model I (Sig.=0.304>0.0005) and Model II (Sig.=0.119>0.0005) do not give adequate and better predictions than those we could infer from the marginal probabilities for the outcome categories.

The Goodness- of- Fit includes the Pearson's chi-square statistic of a model and a chi-square statistic based on deviance. Large significant values show that the observed data and the model predictions are similar. However, the Model Fitting Information and the Goodness- of- Fit statistics are not appropriate when estimating models with continuous covariates, since they are too sensitive to empty cells (Spais & Vasileiou, 2006). Due to the existence of empty cells in the current study, it is uncertain if these statistics follow the chi-square distribution and the significant values could be inaccurate. For this reason, the pseudo R-squares (R^2) were used to assess the overall goodness of fit of the four models. In ordinal regression models, the pseudo R^2 are based on likelihood ratios. The following three methods are used to estimate the coefficient of determination. A generalization of the measure designed to apply when maximum likelihood estimation is used as with ordinal regression is Cox and Snell's R^2 (Cox & Snell, 1989). Nagelkerke R^2 (Nagelkerke, 1991) modifies the index to take values from 0 to 1. The log-likelihood ratio of McFadden R^2 (McFadden, 1973) is one minus the ratio of the full-model log-likelihood to the intercept-only log-likelihood. A low R^2 indicates that the model is likely to be a poor predictor of the outcome for any particular user.

Tab. 4 indicates that Model IV, including all explanatory variables, predicts better the impact of social media use on the participants' activity/mobility plans than the rest three models. Also, Modell III, which includes the participants' social media usage characteristics, predicts better the impact of social media use on activity/mobility plans compared to Model I, which includes the demographic characteristics, and Model II, which includes the travel characteristics. Models III and IV have demonstrated higher values of Nagelkerke R^2 than previous researches (Milioti, et al., 2019).

Table 4: Pseudo R- squares of Models I, II, III and IV				
	Model I	**Model II**	**Model III**	**Model IV**
Cox and Snell	0.016	0.014	0.176	0.204
Nagelkerke	0.017	0.015	0.193	0.223
McFadden	0.006	0.006	0.079	0.093

For the four models, the test of parallel lines compares the estimated model with one set of coefficients for all categories to a model with a separate set of coefficients for each category. The Null Hypothesis refers to the constrained model, which assumes that the lines are parallel. If the lines are parallel, the observed significance level for the change should be large, since the general model does not improve the fit very much. In the four models, the null hypothesis that the lines are parallel is not rejected, since Sig. >0.05 in all models. If Sig. <0.05 then the null hypothesis would be rejected which means that the selected link function is incorrect or the relationships between the independent variables and logits are not the same for all logits.

The parameter estimates for Model IV are given in Table 5 and are the core of the output that shows the relationship between the explanatory variables and the outcome. The column "Estimate" contains the logit regression coefficients. The last category of each input variable was used as reverence value and due to the zero values are not included in the table. The significance values that are less than 0.05, suggesting that their observed effect is not random.

Participants who are younger than 18 years old are less likely to change their mobility plans based on social media information than older participants. An explanation regarding this finding could be related to the fact that this group is more dependent on other members of the household for their travel needs compared to older participants. Furthermore, students and full- time employees are more likely to change their plans after social media use compared to others. The rare public transport use and the minimum time spent on social media has a negative impact on changing mobility plans after using social media as a source of information. According to the results, participants who stated that social media do not help them with the mobility-planning phase have a decreased probability to change their mobility plans upon social media use.

Table 5: Parameter estimates for Model IV		
Input Variable	**Estimate**	**Sig.**
GEN		
Female	-0.077	0.641
AGE		
<18	-1.524	**0.036**
18-25	-0.179	0.643
26-35	-0.160	0.627
36-45	0.067	0.851
OCC		
Student	2.639	**0.037**
Part- time job	2.254	0.077
Full- time job	2.584	**0.038**
Unemployed	2.071	0.109
RES		
Greece	-0.126	0.482
DL		
Yes	0.106	0.600
TM		
Sustainable transport mode users	-0.102	0.562
PTU		
Never	0.085	0.810
Seldom	-0.515	**0.038**
Sometimes	0.231	0.376
Often	-0.100	0.634
DSMU		
Everyday	0.449	0.612
5-6	0.308	0.542
4-3	0.270	0.562

2-1	-0.542	0.071
MSMU		
0-5	-0.558	**0.030**
6-15	-0.364	0.117
16-30	-0.284	0.251
31-60	-0.251	0.390
TSMU		
07:00-12:00	-0.267	0.503
12:00-14:00	-0.390	0.390
14:00-17:00	-0.492	0.212
17:00-00:00	-0.337	0.327
SSOI		
Yes	-0.267	0.304
HOSM		
Never	-3.973	**0.000**
Seldom	-2.960	**0.000**
Sometimes	-1.910	**0.000**
Often	-0.954	**0.001**

4.4. Impact of proposed transport mode based on information provided by social media on mode choice

The next four models were developed to explore the relationship among the impact of the proposed transport mode based on information provided by social media (IPTM) on users' final decision and the i) demographic characteristics ii) travel characteristics iii) social media usage. The dependent ordinal variable was measured on a 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5) and according to descriptive statistics, the mean value was 2.86 (SD= 1.058).

The fifth developed model (Model V) examines the relationship between the impact of the information provided by social media regarding a transport mode on mode choice and the demographic characteristics.

Model V: $(IPTM) = f\ (GEN, AGE, OCC, RES)$. The fifth research hypothesis (H5) is that each of the demographic characteristics is a good determinant of the impact of the proposed transport mode on mode choice.

The next model investigates whether travel characteristics of participants can predict the impact of the proposed transport mode based on information provided by social media on mode choice.

Model VI: $(IPTM) = f\ (DL, TM, PTU)$. The sixth research hypothesis (H6) is that each of the users' travel characteristics is a good determinant of the impact of the proposed transport mode on the final decision.

The seventh model includes as independent variables the participants' responses that are related to social media use. The research hypothesis (H7) is that each of the users' characteristics that are related to social media use predicts better the impact of the proposed transport mode on mode choice.

Model VII: $(IPTM) = f\ (DSMU, MSMU, TSMU, SSOI, HOSM)$

The final model includes all the independent variables of the above-mentioned models.

The last research hypothesis (H8) is that the impact of the proposed transport mode based on information provided by social media on mode choice is predicted by all the characteristics.

Model VIII:

$(IPTM) = f\ (GEN, AGE, OCC, RES, DL, TM, PTU, DSMU, MSMU, TSMU, SSOI, HOSM)$

The Logit link function was selected to run the ordinal regression analysis of the models since the responses were evenly distributed (Fig. 2). Cells with zero frequencies were detected for these models too. The Model Fitting Information of the four models were examined to find out if the models give adequate predictions. The significant chi-square statistics indicate that all the four models give a significant improvement over the baseline intercept-only model. The pseudo R- squares (R^2) were used to assess the overall goodness of fit of the four models.

Figure 2: Histogram of the impact of the proposed transport mode by social media information, on mode choice
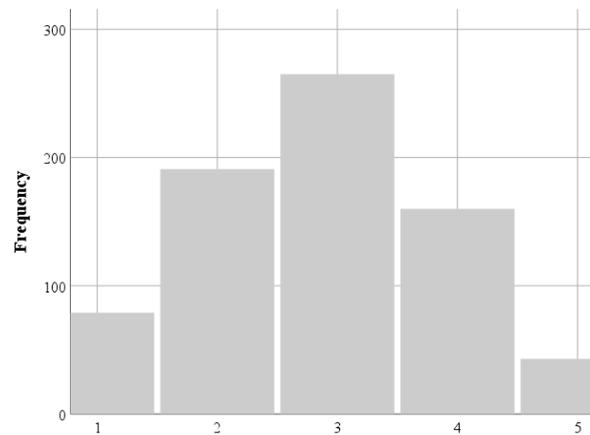
According to Table 6, the last model predicts better the impact of the proposed transport mode based on information provided by social media on mode choice. More analytically, the demographic (Model V) and travel (Model VI) characteristics of a user and the social media usage (Model VII) cannot predict the impact of the proposed transport mode on activity/mobility plans as well as the last model (VIII) does, where all the characteristics are taken into account. A close Nagelkerke R^2 value to a relevant study was achieved for Model VIII (11).

Table 6: Pseudo R- squares of Models V, VI, VII and VIII				
	Model V	**Model VI**	**Model VII**	**Model VIII**
Cox and Snell	0.027	0.040	0.131	0.171
Nagelkerke	0.028	0.043	0.128	0.181
McFadden	0.009	0.014	0.048	0.064

For the four models, the test of parallel lines showed that the proportional odds assumption has been held, as all the Sig. values were higher than 0.05. The parameter estimates for Model VIII are given in Table 7. These parameters show the relationship between the explanatory variables and the outcome. Significance values less than 0.05 were observed in DL, PTU and HOSM independent variables. More specifically, participants that hold a driver's license are less likely to change their mobility plans based on social media information about a proposed transport mode. Furthermore, respondents that use public transport rarely or sometimes are less likely to change their mobility plans compared to those who use public transport always. As expected, the proposed transport mode has a significantly high negative impact on participants who stated that social media never help them with the mobility-planning phase compared to those who stated that social media always help them. It is noted that the absolute values of the parameter estimates for HOSM are decreasing as the ordinal scale increases. This finding is in line with previous researches who stated that respondents who rate highly the social media use are more likely to change their trip plans based on the information provided on social media (Milioti, et al., 2019).

Table 7: Parameter estimates for Model VIII		
Input Variable	Estimate	Sig.
GEN		
Female	-0.115	0.462
AGE		
<18	-0.964	0.165
18-25	0.130	0.724
26-35	-0.079	0.802
36-45	-0.005	0.988
OCC		
Student	-0.854	0.452
Part- time job	-0.792	0.489
Full- time job	-0.713	0.523
Unemployed	-0.196	0.866
RES		
Greece	0.306	0.072
DL		
Yes	-0.443	**0.022**
TM		
Sustainable transport mode users	-0.131	0.436
PTU		
Never	-0.588	0.080
Seldom	-0.917	**0.000**
Sometimes	-0.518	**0.024**
Often	-0.325	0.105
DSMU		
Everyday	0.615	0.467
5-6	0.534	0.267
4-3	0.639	0.149
2-1	-0.085	0.767
MSMU		
0-5	-0.215	0.379
6-15	-0.312	0.157
16-30	-0.314	0.181
31-60	-0.396	0.154
TSMU		
07:00-12:00	-0.010	0.978
12:00-14:00	0.072	0.869
14:00-17:00	0.250	0.506
17:00-00:00	0.297	0.364
SSOI		
Yes	-0.154	0.533
HOSM		
Never	-3.058	**0.000**
Seldom	-2.113	**0.000**
Sometimes	-1.328	**0.000**
Often	-0.542	**0.040**

5. Conclusions

Social media content and interaction with other users has intensified changes in users' activity and mobility plans by setting a new framework for travel behavior. Based on ordinal regression analysis, the current study explored (i) the impact of social media use on activity and mobility planning and (ii) the impact of the proposed transport mode based on information provided by social media on mode choice. According to models' results, participants under 18 years old are not likely to adjust their activity and mobility plans based on social media information as compared to older users. On the contrary, students and full-time employees have an increased probability to change their plans based on information provided by social media. Respondents who seldom or sometimes use public transport are affected less by social media information as related to the proposed transport mode compared to those

who always use public transport. Finally, participants that stated that social media always help them with their activity and mobility planning are affected more by social media information.

Social media usage aspects are better associated with estimating their influence in activity and mobility planning and mode choice. Also, prediction power increases as more independent variables are taken into account. This is a direction to which future work should be oriented.

As social media use is growing, investigation of how influential social media are in mobility decision making is critically important. The findings of this survey are expected to assist the promotion of sustainable urban mobility, as social media is a promising way to reach a large number of people and spread awareness and transport-related information to them.

Limitations

A study limitation is that it is based on self-report data. The definition of some independent variables such as "average minutes spending when using a social media platform", might limit the scope of the study. Although the responses measured the average time accurately, it is uncertain whether users are active all the reported time. Thus, the definition of "social media use" might not reflect the complexity of someone's use patterns.

Data availability statement

The datasets analyzed during the current study are not publicly available due to individual privacy issues but are available from the corresponding author, MK, upon reasonable request.

Funding

Author contributions

The authors confirm contribution to the paper as follows: study conception and design:M. Karatsoli, E. Nathanail; data collection: M. Karatsoli; analysis and interpretation of results: M. Karatsoli, E. Nathanail; draft manuscript preparation: M. Karatsoli. E. Nathanail. All authors reviewed the results and approved the final version of the manuscript.

Citation information

References

Abbasi, A., Rashidi, T.H., Maghrebi, M., & Waller, S.T. (2015). Utilising Location Based Social Media in Travel Survey Methods: bringing Twitter data into the play. *In 'LBSN@SIGSPATIAL/GIS'(A. Pozdnoukhov, D. Sacharidis and S. Xu, eds.), ACM. ISBN: 978-1-4503-3975-9*, 1:1-1:9.

Axsen, J., & Kurani, K.S. (2012). Social influence, consumer behavior, and low-carbon energy transitions. *Annual Review of Environment and Resources*, 37, 311-340.

Axsen, J., & Kurani, K.S. (2014). Social influence and proenvironmental behavior: the reflexive layers of influence framework. *Environment and Planning B: Planning and Design*, 41(5), 847-862.

Ayeh, J.K., Au, N., & Law, R. (2013). Predicting the intention to use consumer-generated media for travel planning. *Tourism Management*, 35, 132-143.

Belgiawan, P. F. Schmöcker, J. D. Abou-Zeid, M. Walker, J. Lee, T. C., Ettema, D. F., & Fujii, S. (2014). Car ownership motivations among undergraduate students in China, Indonesia, Japan, Lebanon, Netherlands, Taiwan, and USA. *Transportation*, 41(6), 1227-1244.

Bingham, C.R., Simons Morton, B.G., Pradhan, A.K., Li, K., Almani, F., Falk, E.B., Shope, J.T., Buckley, L., Ouimet, M.C., & P. T. Albert, P. T. (2016). Peer passenger norms and pressure: experimental effects on simulated driving among teenage males. *Transportation Research F: Traffic Psychology and Behaviou*r, 41, 124-137.

Booth, L., Norman, R., & Pettigrew, S. (2019). The potential implications of autonomous vehicles for active transport. *Journal of Transport & Health*, 15, doi: 10.1016/j.jth.2019.100623

Bregman, S. (2012). *Uses of social media in public transportation*. Transit Cooperative Research Program (TCRP) Synthesis Transportation Research Board, Washington, D. C.

Byon, Y. –J., Abdulhai, B., & Shalaby, A. (2009). Real-time transportation mode detection via tracking global positioning system mobile devices. *Intelligent Transportation Systems*, 13 (4), 161-170.

Chung, N., & Koo, C. (2015). The use of social media in travel information search. *Telematics and Informatics*, *32*(2), 215-229.

Cohen-Blankshtain, G., & Rotem-Mindali, O. (2016). Key research themes on ICT and sustainable urban mobility. *International Journal of Sustainable Transportation*, *10*(1), 9-17.

Cottrill, C. (2017). Tweeting Transit: An examination of social media strategies for transport information management during a large event. *Transportation Research Part C: Emerging Technologies,* 77, 421-432.

Cox, D.R., & Snell, E. J. (1989). *Analysis of Binary Data*. 2nd Edition, Chapman and Hall/CRC, London.

D'Ambra, L., Crisci, A., Meccariello, G., Ragione, L.D., & Palma, R. (2020). Evaluation of the social and economic impact of carbon dioxide (CO_2) emissions on sustainable mobility using cumulative ordinal models: trend odds model. In: *Socio-Economic Planning Sciences*, doi: 10.1016/j.seps.2020.100817

Delbosc, A. & Currie, G. (2014). Changing demographics and young adult driver license decline in Melbourne, Australia. *Transportation*, 41(3), 529-5

Esztergár-Kiss, D., & Tettamanti, T. (2019). Stakeholder engagement in mobility planning. In: *Autonomous vehicles and future mobility*. Elsevier, ISBN: 9780128176962, 113-123.

Fu, K., Nune, R., & Tao, J. X. (2015). Social media data analysis for traffic incident detection and management. In: *Transportation Research Board 94th Annual Meeting*, Washington D.C., 14–4022.

Fu, K., Nune, R., & Tao, J.X. (2015). Social media data analysis for traffic incident detection and management. In: *Transportation Research Board 94th Annual Meeting*, Washington D.C., 14–4022.

Gao, H., Tang, J., & Liu, H. (2012). Exploring social-historical ties on location-based social networks. In *Proceedings of the Sixth International AAAI Conference on Weblogs and Social Media*.

Germann Molz, J. (2012). Travel connections: Tourism, technology and togetherness in a mobile world. London, Routledge. ISBN: 9780203123096.

Goetzke, F., & Weinberger, R. (2012). Separating contextual from endogenous effects in automobile ownership models. *Environment and Planning A: Economy and Space*, 44(5), 1032-1046.

Gossling S., & Stavrinidi, I. (2015). Social Networking, Mobilities, and the Rise of Liquid Identities. Mobilities, 11(5), 723-743.

Gossling, S. (2017). ICT and transport behaviour: A conceptual review. *International Journal of Sustainable Transportation*, 12(3), 153-1

Gunnarsson, S. O. (2000). Studies in travel behaviour and mobility management need a special scientific discipline: "Mobilistics". IATSS Research, 24, 69- 75.

Gutiérrez, P. A., Pérez-Ortiz, M., Sánchez-Monedero, J., Fernández-Navarro, F., & Hervás Martínez, C. (2016). Ordinal regression methods: Survey and experimental study. In: *IEEE Transactions on Knowledge and Data Engineering*, 28, 127-146.

Hasan, S., Zhan, X., & Ukkusuri, S.V. (2013). Understanding urban human activity and mobility patterns using large-scale location-based data from online social media. In: *Proceedings of the 2nd ACM SIGKDD International Workshop on Urban Computing*, ACM.

Hasan, S., & Ukkusuri, S.V. (2015). Location contexts of user check-ins to model urban geo life-style patterns. *PLoS ONE, 10*(5) , p. e0124819.

Hosmer Jr., D.W., Lemeshow, S., & Sturdivant, R.X. (2013). *Applied Logistic Regression*. (3rd Edition). Wiley Series in Probability and Statistics. John Wiley & Sons, 2013.

Keith, D., Sterman, J., & Struben., J. (2012). Understanding spatiotemporal patterns of hybrid-electric vehicle adoption in the United States. *91st Annual Meeting of the Transportation Research Board*.

Lee J.H., Davis, A.W., McBride, E., & Goulias, K.G. Exploring Social Media Data for Travel Demand Analysis: A comparison of Twitter, household travel survey and synthetic population data in California. Paper presented at the 96th Annual Meeting of the Transportation Research Board, Washington, D.C., 20

Lee, J.H., A. Davis, S. Y. Yoon, K. G. Goulias: Activity Space Estimation with Longitudinal Observations of Social Media Data. In*: Transportation Research Board 95th Annual Meeting*, 16-0070, 2016.

Line, T., Jain, J. & Lyons, G. (2011). The role of ICTs in everyday mobile lives. *Journal of Transport Geography,* 19(6), 1490-1499.

Manca, M., Boratto, L., Roman, V. M., Martori i Gallissà, O., & Kaltenbrunner, A. (2017). Using social media to characterize urban mobility patterns: State-of-the-art survey and case-study, *Online Social Networks and Media*, 1, 56-69.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behaviour. In *Frontiers in Econometrics* (P. Zarembka, ed.), Academic Press New York, 105-142.

Milioti, C., Katopodis, V., Kepaptsoglou, K., & Tyrinopoulos, Y. (2019). Assessing the influence of social media in tourist mobility of young travelers. *Presented at 98th Annual Meeting of the Transportation Research Board,* Washington, D.C.

Mohammadreza, M. (2012). A study on effects of demographic variables on success of social media. *Management Science Letters,* 2, 2557-2564.

Nagelkerke, N. J. D. (1991). A Note on a General Definition of the Coefficient of Determination. *Biometrika*, 78, 691-692.

Osborne, J. W. (2015). Best Practices in Logistic Regression. *Best practices in logistic regression*. 55 City Road, London: SAGE Publications.

Schroeder, A., & Penninghton-Gray, L. (2014). The Role of Social Media in International Tourist's Decision Making. *Journal of Travel Research*, 54, 584-595.

Simms, A. (2012). Online user- generated content for travel planning- different for different kinds of trips?. *e- Review of Tourism Research, 10*(3), 76-85.

Spais, S. G., & Vasileiou, K.Z. (2006). An ordinal regression analysis for the explanation of consumer overall satisfaction in the food-marketing context: The managerial implications to consumer strategy management at a store level. *Database Marketing & Customer Strategy Management*, 14, 51-73.

Staus, A. (2008). An ordinal regression model using dealer satisfaction data. *Journal of Economics*, 112, 168-172.

Stewart, G., Kamata, A., Miles, R., Grandoit, E., Mandelbaum, F., Quinn, & C., Rabin, L. (2019). Predicting mental health help seeking orientations among diverse Undergraduates: An ordinal logistic regression analysis. *Journal of Affective Disorders,* 2271-280.

Tasse, D., & Hong, J. I. (2018). Using social media data to understand cities. Carnegie Mellon University. *Journal contribution*, doi:10.1184/R1/6470645.v1

Tian, Y., Zmud, M., Chiu, Y.C., Carey, D., Dale, J., Smarda, D., Lehr, R., & James, R. (2016). Quality assessment of social media traffic reports – a field study in Austin, Texas. In: *Transportation Research Board 95th Annual Meeting*, Washington D.C., 16-6852.

van den Berg, P., Sharmeen, F., & Weijs-Perrée, M. (2017). On the subjective quality of social Interactions: Influence of neighborhood walkability, social cohesion and mobility choices. *Transportation Research Part A: Policy and Practice, 106*, 309-319.

van Wee, B. (2015). Peak car: the first signs of a shift towards ICT-based activities replacing travel? A discussion paper. *Transport Policy*, 42, 1-3.

Xiang, Z., & Gretzel, U. (2010) Role of social media in online travel information search. *Tourism Manageme*nt, 31: 179-188.

Yamagishi, Y., Saito, K., & T. Ikeda, T. (2016). Modeling of Travel Behavior Processes from Social Media. *PRICAI 2016: Trends in Artificial Intelligence. Lecture Notes in Computer Science*, 9810, 626-637.

Yoo, H.-H., & Gretzel, U. (2011). Influence of personality on travel-related consumer-generated media creation. *Computers in Human Behavior*, 27, 609-621.

Yoo, K.-H., & Gretzel, U. (2012). Use and Creation of Social Media by Travellers. In: *Social Media in Travel, Tourism and Hospitality: Theory, Practice and Cases* (M. Sigala, E. Christou, and U. Gretzel, eds.), Ashgate Pulsihing Limited, Surrey, UK, 189-206.

Zhang, Z., Tang, Z., T. Q., & Huang, H.-J. (2019). Modeling the social-influence-based route choice behavior in a two-route network. *Physica A: Statistical Mechanics and its Applications*, 531, 121744.