



Investigating the temporal changes in the relationships between time spent on the internet and non-mandatory activity-travel time use

Guoqiang Wu¹ · Jinhyun Hong² · Piyushimita Thakuriah³

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Abstract

The amount of time we spend online has been increasing dramatically, influencing our daily travel and activity patterns. However, empirical studies on changes in the extent to which the amount of time spent online are related to changes in our activity and travel patterns are scarce, mainly due to a lack of available longitudinal or quasi-longitudinal data. This paper explores how the relationships between the time spent using the Internet, and the time spent on non-mandatory maintenance and leisure activities, have evolved over a decade. Maintenance activities include out-of-home activities such as shopping, banking, and doctor visits, while leisure activities include entertainment activities, visiting friends, sporting activities, and so forth. Our approach uses two datasets from two major cross-sectional surveys in Scotland, i.e. the 2005/06 Scottish Household Survey (SHS) and the 2015 Integrated Multimedia City Data (iMCD) Survey, which were similarly structured and formed. The multiple discrete–continuous extreme value (MDCEV) model and difference-in-differences (DD) estimation are applied and integrated to examine how the relationships between the time spent on the Internet and travel have changed over time and the direction and magnitude of the changes. Our findings suggest that the complementary associations between Internet use and individuals' non-mandatory activity-travel time use are diminishing over time, whereas their substitutive associations are increasing. We additionally find that such temporal changes are significant in the case of those who spent moderate to high levels of time on the Internet (5 h or more online) per week.

Keywords Non-mandatory activities · Travel time use · Internet use · Temporal changes · MDCEV model · Difference-in-differences estimation

Introduction

Since at least the 1970s, researchers have made extensive efforts to better understand different aspects of the complex relationships between the use of information and communications technologies (ICT) and individuals' activity and travel behavior. In the current

✉ Guoqiang Wu
g.wu@leeds.ac.uk

Extended author information available on the last page of the article

information age, such research efforts are facing new challenges due to the ubiquity of modern technology and the multiple ways in which ICT use is increasingly deeply embedded into our daily lives (Reed 2014). Due to the rapidly changing technology landscape, we can expect changes in people's use of ICT over time. A good illustration of this fact is the expansion of the e-commerce market, in which transaction strategies are evolving from the model of business-to-business (B2B) via business-to-customer (B2C) to the model of customer-to-customer (C2C) (Basole and Rouse 2008). Consequently, individuals are finding e-commerce easy to use and online transactions easier to make, and therefore are becoming more dependent on them in their everyday lives. From a long-term perspective, this rapid evolution in technologies would bring about changes in people's lifestyles and behavior over time, including in their mobility behavior (El Zarwi et al. 2017).

Moreover, the extent to which people spend time on various online activities has been changing dramatically for over a decade. A report by the Office of Communications (Ofcom) showed that time spent online doubled from around 10 h per week in 2005 to over 20 h per week in 2013 (Ofcom 2015). A more recent report indicated that the total average daily time spent on the Internet in the UK was approximately three hours in 2018 (Ofcom 2019). The existence of time constraints such as total time available during the day implies that the increased time spent online may be accompanied by a respective decrease in time spent performing other activities, including physical activities and travel. Nevertheless, there appears to be a dearth of transport studies taking such a dynamic or temporal perspective in examining the relationships between the use of time on ICT and travel, as the majority of existing studies on this topic adopt a cross-sectional approach.

Furthermore, most studies utilize relatively simple measures of ICT use (e.g. Internet connections, frequency of different types of Internet use, etc.). This situation has largely resulted from a lack of data sources that either contain repeated information on the same individuals over time (panel data) or repeated samples from the same population (repeated cross-sectional data) that simultaneously record patterns of ICT use and travel behavior characteristics (Pawlak et al. 2015). Additionally, difficulties arise in capturing the rapid revolution of ICT functionalities or adoption, which may have also contributed to the scarcity of longitudinal studies.

Regardless of these challenges and difficulties, examining the relationship between the time spent using ICT and individuals' mobility behavior from a temporal perspective is essential to gaining a comprehensive understanding of how these relationships may evolve, particularly as technologies are evolving rapidly and the time people dedicate to ICT is changing significantly. This study aims to contribute to such research by analyzing how, given the changes in the amount of time people dedicate online over time, people are spending different amounts of time on maintenance and leisure activities as well as daily travel to perform those activities. We use combined datasets derived from two similarly structured household surveys in Scotland, which are drawn from the same sampling frame: the 2005/06 Scottish Household Survey (SHS) and the 2015 Integrated Multimedia City Data (iMCD) survey. The same survey company conducted both surveys and the iMCD used the SHS as a reference. The study makes use of the techniques of the multiple discrete–continuous extreme value (MDCEV) model and the difference-in-differences (DD) estimation to explore the temporal changes in the effects of Internet use on individuals' activity–travel time use over a decade. Since all the dataset information on individuals' use of the Internet only suggest their usage for non-work purposes, travel behavior characteristics examined in this study are for non-work or non-mandatory activity purposes. More specifically, this study attempts to answer two primary questions. First, have the relationships between the time spent on the Internet and activity–travel time use for non-mandatory

(maintenance and leisure) purposes changed during the period between 2005/06 and 2015? And second, if so, how have these relationships changed over time? The paper is organized as follows: “[Literature review](#)” provides a review of existing studies on temporal changes in ICT-travel relationships, “[Data and variables](#)” provides more detailed information on the empirical data and variables used in this study, “[Methods and models](#)” explains the analytical methods of the MDCEV model and the DD estimation applied in this study, “[Results and findings](#)” presents model results and findings, and “[Summary and conclusions](#)” concludes the analysis.

Literature review

Although most studies on the interactions between ICT use and mobility behavior have been performed from a cross-sectional perspective, some research, fueled by the availability of longitudinal data, has taken a temporal approach to investigate evolutions in such interactions over time. Generally, these longitudinal analyses are based on the fact that there is increasing advancement and adoption of ICT for daily use, which may lead to dynamic effects on activity-travel behavior over time.

Hamer et al. (1991) were pioneers in examining the temporal dynamics in the effects of ICT adoption on travel behavior. They conducted an experimental panel study to monitor the changes in teleworkers’ travel behavior over five waves of data collection performed in approximately three-month intervals between 1990 and 1991. Their findings suggested that teleworking resulted in a 17% decrease in the total number of trips and a 26% reduction in peak-hour car use by teleworkers.

Mokhtarian and Meenakshisundaram (1999) applied a disaggregate longitudinal structural equations model (SEM) to analyze the complex interactions between the amount of travel and different forms of communication, including personal meetings, transfer of an information object, phone, fax, and email, over the period between 1994 and 1995. They found no significant cross-sectional or longitudinal relationships between electronic forms of communication and personal meetings or trips. In contrast, Choo and Mokhtarian (2007) examined the aggregate relationships between telecommunications (number of local phone calls) and travel (passenger vehicle-miles traveled) by using structural equation modeling of national time-series data (1950–2000) in the U.S. The findings of this study suggested that such aggregate relationships were due to complementarity—as telecommunications demand increases, travel demand increases, and vice versa.

Kim and Goulias (2004) also employed the SEM approach to investigate the relationships between time use for daily activities and travel, daily frequencies of travel mode use, and changes in ICT use between 1997 and 2000 using Puget Sound Transportation Panel (PSTP) data. They found that the effects of changes in ICT use depended on the location of the technology used (home or workplace) and its mobility. For instance, new computer users at the workplace tended to spend more time on subsistence activities and less time on leisure, while new computer users at home generally dedicated more time to all activities and tended to use public transit more frequently.

Based on Swedish National Communication Survey data (1997–2001), Thulin and Vilhelmson (2006) performed a longitudinal analysis to examine the effects of young people’s changing usage of ICT on their in-home and out-of-home activity engagement over time. Their findings suggested that increased computer use during the study period had no clear

effects on young people's time use for out-of-home activity participation, but it significantly displaced other in-home activities.

Similarly, Wu et al. (2019) explored how changes in young people's use of the Internet while transitioning from adolescence to adulthood were related to sustainable travel patterns in their adulthood. Based on the longitudinal datasets derived from the 2004 British Household Panel Survey and the Understanding Society Survey (Wave 4, 2012/14), they developed an SEM to assess the complex relationships between young people's Internet use over time, their travel mode use, and their environmental attitudes and behaviors. The findings showed that consistent heavy use of the Internet from adolescence to young adulthood was correlated with the formation of environmental attitudes, which were indirectly but significantly associated with young adults' sustainable travel patterns.

The above studies, which designed and carried out empirical analyses from a temporal perspective, have provided an approach to gaining insights into the dynamic nature of the interactions between ICT use and mobility behavior that are unlikely to be achieved by cross-sectional analyses. They can capture not only the causal structure of ICT-travel interactions but also the extent and pace of the changes in these interactions over time. Nevertheless, those studies rely on longitudinal or panel datasets, which are relatively scarce and difficult to acquire in research practices. Hence, findings on the temporal dynamics in ICT-travel relationships might be limited due to the availability of such data. Since repeated cross-sectional (RCS) datasets, which are comparatively common in the current research context, add temporal dynamics to traditional cross-sectional data by repeatedly recording the same (or similar) information for different samples of individuals each time, they could also enable the investigation of changes in behavior and relationships over time. Pawlak et al. (2015) provided a good example by developing a method of pooling independently collected cross-sectional datasets across time (PICSaT) and using UK Opinions and Lifestyle Survey data from the period between 2005 and 2010 (RCS data). Based on the PICSaT approach, they employed structural equation models to examine the changes in the interactions between different ICT adoptions and travel behavior over time.

Additionally, although those studies have analyzed various aspects of ICT usage and their effects on physical travel, they have not examined and modeled the relationships between the amount of time spent on using ICT and travel behavior. As Hong and Thakuriah (2016) pointed out, the rapidly increasing amount of time spent online would significantly change people's daily activity-travel patterns as people have a limited daily time budget. Therefore, it might be necessary to investigate the effects of ICT use on travel from the dimension of time use. This study will fill those gaps identified in existing research on the evolutions in the ICT-travel interactions across time.

Data and variables

The datasets utilized in this study are from two major household surveys implemented in Scotland: the 2005/06 Scottish Household Survey (SHS) and the 2015 Integrated Multimedia City Data (iMCD) survey. SHS is a continuous household survey that began in 1999. This survey collects up-to-date information on Scottish households (e.g. composition, attitudes, finance) as well as individual travel patterns. It was initially based on two-year rolling samples but changed to a one-year basis survey from 2012. The iMCD survey is part of a multi-strand data infrastructure project conducted by the Urban Big Data Centre at the University of Glasgow (Thakuriah et al. 2020). The survey includes multi-topic household

and person-level information as well as a one-day travel diary. The primary reason for adopting two survey databases instead of relying on the SHS alone with a selection of its two cross-section waves is because the critical information for this study—the amount of time spent on the Internet—was no longer included as part of the SHS after 2006. Targeting eight local authority areas of Glasgow and Clyde Valley (GCV) in Scotland, the iMCD survey used the same methodologies developed by the SHS (2012 onwards) such as survey structuring, data collection, and weighting (Ipsos MORI 2015), though it included household and individual cases different from the SHS.

More importantly, the iMCD surveyed individuals' time use on the Internet in 2015 by re-adopting the question that was removed in later SHS waves. Both surveys provide up-to-date information on the composition, characteristics, attitudes, and behavior of Scottish households and individuals, mainly consisting of two questionnaire sections. The household reference person, who is the highest income householder (HIH) or his/her spouse/partner, completed the first section of the survey questionnaire that dealt with topics related to the overall conditions of the household, such as household composition, total income, housing and tenure, vehicles available to the household, and access to the Internet. Adults in the household then completed the second part of the interview dealing with individual issues regarding, for example, socio-demographics, personal income, travel, use of public transport, and the Internet. In both surveys, the interviewed adults were asked to complete a travel diary, which collects detailed information on personal travel the interviewees made for private purposes or work/education on the day before the interview (e.g. start and end time of each journey, origin and destination of each journey, and travel mode use). One difference between the two surveys is that SHS only interviewed one random adult from each household to collect individual and travel information while the iMCD survey interviewed all adults from a household.

To further examine the comparability of the two surveys, the socio-demographics of respondents from the 2015 iMCD survey and the 2015 SHS for the same local authorities covering GCV are summarized and compared in Table 1. The statistics appear to show that the main demographic characteristics revealed by the two surveys are quite analogous. Further T-tests have been run to determine if there are any significant differences between the mean/percentage statistics of the two survey samples. The results suggest that the two groups of statistics are not statistically different at the 0.05 level of significance. Therefore, the 2015 iMCD survey could be treated as a continuation of the early SHS (pre-2007), which contains information about people's time use on the Internet and targets the GCV region. Investigation of the temporal changes in ICT-travel relationships over a decade is therefore achievable by using the data from the 2005/06 SHS (the GCV sample) and the 2015 iMCD survey. A total of 2,095 individual interviews were conducted in the iMCD survey, while the GCV sample size of the 2005/06 SHS was 8,436.

The variables considered in this study include activity-travel time use, use of the Internet, socio-demographics, residential location, and travel date. While individuals' travel time was indicated as journey duration in minutes for each trip on a given day in the travel diary datasets of the two surveys, time use for out-of-home activity participation was calculated by subtracting the arrival time of the last trip from the departure time of the next trip. Additionally, 21 activity types in the original dataset, recorded as the purposes for each journey for each person, were classified into three activity categories based on previous studies and practices analyzing activity-travel time use (Reichmann 1976; Lu and Pas 1999; Srinivasan and Bhat 2005; Wang and Law 2007), namely: mandatory/subsistence activities (e.g., work, studying at school/college, attending training schemes), maintenance activities (e.g., shopping, banking, doctor visits, picking-up/dropping-off children), and

Table 1 Comparison of demographics of respondents between the 2015 iMCD survey and the 2015 SHS (Glasgow and Clyde Valley samples)

	2015 iMCD		2015 SHS (GCV samples)	
	Mean/percentage	SD	Mean/percentage	SD
Age	49.42	18.91	50.93	18.42
16–24	11.55%		10.10%	
25–34	14.42%		14.11%	
35–44	15.89%		15.17%	
45–59	25.87%		26.56%	
60–74	21.62%		22.34%	
75 +	10.65%		11.72%	
Gender				
Male	45.68%		44.76%	
Female	54.32%		55.24%	
Employment status				
Self employed	5.12%		4.17%	
Employed full time	32.68%		34.18%	
Employed part time	8.66%		10.85%	
Looking after the home/family	5.07%		4.97%	
Permanently retired from work	28.09%		29.64%	
Unemployed and seeking work	7.03%		3.94%	
At school	1.10%		0.76%	
In further/higher education	5.64%		3.37%	
Government work/training scheme	0.00%		0.01%	
Permanently sick or disabled	3.49%		6.35%	
Unable to work due to short-term illness	1.72%		1.16%	
Other	1.40%		0.60%	
Household size	2.23	1.26	2.13	1.18
Number of kids in household	0.43	0.85	0.40	0.79
Number of cars in household				
0	33.33%		36.50%	
1	42.24%		40.53%	
2	19.31%		18.97%	
3 and plus	5.12%		4.00%	
Living in urban areas	94.13%		96.41%	
Sample size	2095		2756	

leisure activities (e.g., visiting friends, sporting activities, day trips, entertainment activities). As a result, individuals' time use regarding activity engagement and trip making for mandatory and non-mandatory purposes became available. While activity-travel time use for non-mandatory purposes (maintenance and leisure purposes) was examined as a dependent variable in this study, time spent on outdoor mandatory activities was considered an independent variable because mandatory activities could largely determine the patterns of undertaking other activities and associated trip making (Hägerstrand 1970; Cullen and Godson 1975; Bhat et al. 2004). For modeling purposes, along with the time spent on

each of the aforementioned activities and trips, the time spent on “other” activities that include any other types of daily activities, such as in-home activities without travel requirements, was also computed by subtracting the total amount of time spent on outdoor mandatory and non-mandatory activities and associated trips, and daily sleep duration (assumed to be seven hours a day) from the total daily time budget ($24 \times 60 = 1440$ min). Furthermore, as many studies (Bhat and Misra 1999; Schlich and Axhausen 2003; Zhong et al. 2008; Gim 2018) have shown that individuals’ activity-travel behaviors for different purposes vary greatly between weekdays and weekends, the date of performing the activity and trip making (weekdays or weekends) was also included as an independent variable in this study.

In terms of individuals’ usage of the Internet, both the 2005/06 SHS and 2015 iMCD survey asked about the amount of time people spent weekly on the Internet for non-work purposes. However, this usage is represented by time-use intervals (“never use,” “up to 1 h,” “from 1 h up to 5 h,” “from 5 h up to 10 h,” “from 10 h up to 20 h,” and “over 20 h”) in the 2005/06 SHS dataset, while in the iMCD survey dataset the exact amount of time is indicated. The 2005/06 SHS classification was adopted to generate a categorical variable with six time-use categories for the iMCD sample to unify the measurements in the analysis. After removing all the cases with missing or invalid information regarding Internet use and activity-travel time use, the size of the individual sample was reduced to 1484 for the 2015 iMCD data and 5006 for the 2005/06 SHS-GCV data.

Apart from the key variables of activity-travel time use and Internet use, seven socio-demographic variables are also considered as controlled variables in this study including age, gender, number of children, cars in the household, availability of a valid driving license, annual personal income, and employment status. Since inflation effects lead to the growth of nominal income over the years, they need to be eliminated for a better comparison of real income levels in different periods. Therefore, the 2015 income values were adjusted to 2005/06 British Pound values according to the UK Consumer Prices Index published by the Office for National Statistics (ONS). In addition, a categorical variable of residential locations (i.e. urban, town, and rural areas) was included in our model. Lastly, the effects of travel dates and Internet access at home on activity-travel time use were also controlled.

Table 2 shows all the variables included in this study, as well as descriptive statistics of each variable in 2005/06 and 2015. As shown in the table, individual activity duration and travel time for both maintenance and leisure purposes, which are measured in minutes and treated as dependent variables in this study, generally experience decreases on average during the past decade. However, the average time use for undertaking mandatory activities increases moderately over time. In both survey years, the minimum activity-travel time use for each mandatory and non-mandatory activity purpose is zero, suggesting that an individual might not undertake all of those types of outdoor activities on a specific day. By contrast, the minimum values of time use for other activities are greater than zero in both years, implying that all individuals in the two samples spent more or less time on those activities in a day.

In terms of socio-demographic features, the age structure of adult samples in the two surveys is quite similar and middle-aged people account for the largest proportion (around 40%) of the whole sample in both surveys. In both survey periods, females make up a slightly greater proportion than males, accounting for 54–56% of the total sample. While the average number of children in a family slightly decreases from 0.52 in 2005/06 to 0.47 in 2015, ownership of vehicles by a household shows a mild increase during this period from 0.98 to 1.13 vehicles per household on average. As for driver license ownership, the

Table 2 Variables used in the current study and their descriptive statistics over time

	2005/06 (SHS-GCV) Sample			2015 (iMCD) Sample		
	Mean/percentage	Min	Max	Mean/percentage	Min	Max
Activity-travel time use (minutes)						
Maintenance activity duration	59.62	.00	630.00	56.53	.00	618.00
Maintenance travel time	45.34	.00	588.00	39.72	.00	585.00
Leisure activity duration	53.63	.00	612.00	48.21	.00	582.00
Leisure travel time	34.82	.00	584.00	30.65	.00	588.00
Mandatory activity duration	147.61	.00	970.00	160.78	.00	990.00
Other activity duration	670.80	50.00	1015.00	687.40	77.00	1020.00
Socio-demographics						
Age 16–34 (reference)	25.40%	.00	1.00	25.67%	.00	1.00
Age 35–55	41.25%	.00	1.00	39.20%	.00	1.00
Age > 55	33.35%	.00	1.00	35.13%	.00	1.00
Gender (female = 1)	55.96%	.00	1.00	53.81%	.00	1.00
No. of kids	.52	.00	6.00	.47	.00	5.00
No. of vehicles	.98	.00	6.00	1.13	.00	5.00
Driving license (own = 1)	69.58%	.00	1.00	67.75%	.00	1.00
Personal income (thousands of Pounds)	13.24	.00	141.37	11.85	.00	112.18
Employment (employed = 1)	58.32%	.00	1.00	52.28%	.00	1.00
Residential locations						
Urban (reference)	87.94%	.00	1.00	85.99%	.00	1.00
Town	6.09%	.00	1.00	7.88%	.00	1.00
Rural	5.97%	.00	1.00	6.13%	.00	1.00
Internet access at home						
Internet access at home	46.77%	.00	1.00	86.21%	.00	1.00
Travel date (weekdays = 1)						
Travel date (weekdays = 1)	82.33%	.00	1.00	82.81%	.00	1.00
Internet use						
Never (reference)	46.27%	.00	1.00	16.85%	.00	1.00
Up to 1 h	14.97%	.00	1.00	3.17%	.00	1.00
1 up to 5 h	23.01%	.00	1.00	11.32%	.00	1.00
5 up to 10 h	8.93%	.00	1.00	23.92%	.00	1.00
10 up to 20 h	4.40%	.00	1.00	24.12%	.00	1.00
Over 20 h	2.42%	.00	1.00	20.62%	.00	1.00
Sample size						
Sample size	5006			1484		

ownership ratio among the adults in the surveyed region remains stable (around 70%) over time. After adjusting the nominal income values in 2015 for a better comparison, the average annual personal income over the previous decade witnesses a decrease from £13,240 to £11,850. Meanwhile, both the employment rate and rate of city dwellers generally show mild decreases over the ten years. Conversely, the ratio of individuals having access to the Internet at home surges from 47% in 2005/06 to 86% in 2015. In both survey samples, the majority of the respondents (over 80%) reported their daily activity-travel information on weekdays.

As for time spent on the Internet, which is the focus of this study, people generally spent much more time online for personal or non-work purposes at the end of the ten-year period. Although approximately 17% still did not use the Internet for such purposes in 2015, the ratio is much lower in comparison to 46% of non-users in 2005/06. Another substantial change can be seen in the structure of users. In 2005/06, most users spent no more than five hours online per week (i.e. “light users”), while by 2015 the majority could be categorized as “medium-to-heavy users,” dedicating over five hours to the Internet for personal purposes. In 2015, over 20% of adults spent more than 20 h per week online, whereas this proportion was almost negligible (less than 3%) in 2005/06. The Internet was certainly increasingly penetrating individuals’ personal lives during the previous ten-year period.

Methods and models

Two modeling approaches, the MDCEV model and the DD estimation, were applied to investigate the relationships between the amount of time spent on the Internet and individuals’ activity-travel time use, and the temporal changes in such relationships. The adoption and specification of the two models are mainly determined by the research objective and the questions to be addressed, and features of the data and variables considered, which are explained as follows.

Multiple discrete–continuous extreme value (MDCEV) model

In this study, we used the amount of time spent on maintenance and leisure activities and associated travel as dependent variables. On a given day, the existence of temporal constraints may force individuals to decide how to make the most effective use of their available and limited time budget to satisfy their daily needs. Hence, individuals may decide which activities to participate in and how long to perform each activity and associated travel. The previous descriptive analysis (see Table 2) shows that a respondent may not have undertaken all types of activities in a day. For example, approximately 36% and 44% of the individuals in the 2005/06 SHS-GCV sample did not perform any maintenance and leisure activities, respectively, on the day before the survey interview. In the 2015 iMCD sample, such ratios are around 33% and 40%. Considering the existence of the joint decision-making mechanism of individuals’ activity participation and time use allocation behavior, this study employs the MDCEV model.

The multiple discrete–continuous extreme value model and its various extensions were initially proposed by Bhat (2005) to model multiple discreteness simultaneously. It was first developed to estimate individuals’ discretionary time-use decisions on how they allocated continuous amounts of time to participate in various leisure activities (Bhat 2005). Since then, the MDCEV model has been widely applied in transport studies. Examples of applications include activity-travel time use (Kapur and Bhat 2007; Spissu et al. 2009; Chikaraishi et al. 2010; Wang and Li 2011), vehicle holdings and usage (Bhat and Sen 2006; Sen 2006; Imani et al. 2014; Augustin et al. 2015), vacation travel (Wu et al. 2011; Pinjari and Sivaraman 2013), transport expenditure (Pinjari 2011), and social network and communication (Calastri et al. 2017). Apart from transport, the MDCEV model and its extensions have also been used in other fields such as media use (Han et al. 2014; Woo et al. 2014), fuel demand and consumption (Frontuto 2012, 2019), food demand (Richards and Mancino 2014), and alcohol consumption (Lu et al. 2017).

The MDCEV model is formulated based on the utility maximization theory. Different from traditional choice modes, the MDCEV model relaxes the assumption of the alternatives being mutually exclusive by allowing the choice of multiple goods (Calastri et al. 2017). The integration of a discrete and continuous choice dimension in the model facilitates modeling the behavior of individuals choosing multiple options at the same time (e.g., undertaking maintenance and leisure activities and associated trips in a day) and the continuous amount of consumption for each option (e.g., the amount of time spent on activity participation and trip making) simultaneously. It is expected that individuals make their choice and consumption decisions to maximize a direct utility function $U(x)$, where vector x is the quantity of consumption for each of the total k goods/alternatives, $x = (x_1, \dots, x_k)$. The total consumption across the k alternatives is subject to a budget constraint E , which is 1440 min (24 h) in this study. In many empirical analyses, x also includes outside goods that are consumed at least to some degree by all the individuals in the sample and normally considered the base alternative in the model (Bhat 2008; Spissu et al. 2009; Calastri et al. 2017). In this study, such outside goods are the other activities that all individuals have undertaken more or less in a day.¹ The budget constraint can be formulated as follows:

$$\sum_{k=1}^K x_k \leq E \tag{1}$$

Bhat (2008) defines the direct utility (i.e., utility that an individual acquires for allocating the consumption quantity x_k to each of the k alternatives) based on a generalized variant of the translated constant elasticity of substitution (CES) utility function. By assuming alternative 1 to be the outside good, the utility function is expressed as follows:

$$U(x) = \frac{1}{\alpha_1} \psi_1 x_1^{\alpha_1} + \sum_{k=2}^K \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{2}$$

where $U(x)$ is a quasi-concave, increasing, and continuously differentiable function with respect to x , and γ_k , α_k and ψ_k are parameters associated with alternative k . α_k is the satiation parameter that reduces the marginal utility with increasing consumptions of alternative k . It controls the satiation effect by exponentiating the consumption quantity. α_k can take any value that is smaller or equal to 1, and low α_k value suggests faster satiation. γ_k is a translation parameter that determines if corner solutions (an individual has zero consumption for any alternative other than the outside good) or interior solutions (an individual has non-zero consumption quantities for all alternatives) are allowed. Moreover, since γ_k defines a scale for each alternative, it also controls the satiation effect by translating the consumption quantity. That is, a higher value of γ_k suggests fewer satiation effects with respect to the consumption of the corresponding x_k . For example, a higher value of γ_k in our case implies that individuals are less likely to satiate when undertaking activity k and willing to spend more time on activity k . ψ_k represents the baseline marginal utility (i.e., the marginal utility at the point of zero consumption) for an alternative k . A higher baseline utility makes corner solutions less likely. Bhat (2005) defines the random utility function of ψ_k as follows:

¹ The inclusion of other activities in the analysis enables the endogenous estimations of the total time use for the four types of activity-travel pursued for maintenance and leisure purposes.

$$\psi_k = \exp(\beta' z_k + \varepsilon_k) \tag{3}$$

where z_k is a set of attributes characterizing the alternative k and the decision-maker or consumer, and β' is a set of parameters determining their associations with alternative k . ε_k is an extreme value error term.

Although both α_k and γ_k control for satiation levels through different mechanisms, the former does so by exponentiating consumption quantity while the latter by translating it. Bhat (2008) argued that the two effects on satiation are very difficult to disentangle in practice. Hence, he proposed to estimate one parameter instead and set the other parameter at a fixed value, which leads to the α -profile and γ -profile in MDCEV model configurations. In the α -profile models, the γ_k values are constrained to 1 for all alternatives and α_k values are estimated across different alternatives. However, in the γ -profile, α_k values are set to be 0 for all alternatives but the outside goods and γ_k values are estimated for each “inside” alternative $k > 1$. This study adopts the γ -profile model configuration as it was found to provide a better statistical fit.

Based on the parameters specified and estimated above, the probability that an individual consumes the quantities (the amount of time in this study) $x_1^*, x_2^*, \dots, x_M^*, 0, \dots, 0$, where M of the k alternatives are consumed in positive amounts, can be formulated as follows (see Bhat 2008):

$$P(x_1^*, x_2^*, \dots, x_M^*, \dots, 0, \dots, 0) = \frac{1}{p_1} \frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^M f_m \right) \left(\sum_{m=1}^M \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^M e^{V_m/\sigma}}{\left(\sum_{k=1}^K e^{V_k/\sigma} \right)^M} \right) (M-1)! \tag{4}$$

where σ is an estimated scale parameter and $f_m = \left(\frac{1-\alpha_m}{x_m^* + \gamma_m} \right)$.

Difference-in-differences (DD) estimation

The difference-in-differences estimation is a widely used technique to evaluate the effects of a specific intervention or treatment on relevant outcome variables (Abadie 2005; Bertrand et al. 2004). In doing so, it compares the differences in outcomes before and after the treatment for the group affected by the treatment with the same difference for the unaffected group (Bertrand et al. 2004). Therefore, it is normally required to collect data for a “treatment group” and a “control group” in two or more time periods. The DD settings fit our research context, where the Internet users can be seen as the “treatment group”, while the non-users represent the “control group”, and an attempt is made to seek the difference over time in the average difference of activity-travel outcomes with and without the effect of Internet use.

Before applying the DD estimation for this repeated cross-sectional study, the samples from two cross-sectional survey waves, referring to the 2005/06 SHS (Glasgow and Clyde Valley sample) and the 2015 iMCD Survey, were pooled first. As indicated by Wooldridge (2013), using pooled cross-section data increases the sample size, which will generate more precise estimators and test statistics with more power. More importantly, it raises only minor statistical complications when modeling the temporal changes occurring in the same population (Wooldridge 2013). The intercept term of the assumed relationship is normally allowed to differ across periods to reflect the fact that the population may have different distributions at different points in time. It is accomplished by including indicators

or dummy variables for all but the earliest year in the pooled sample, as the earliest year is commonly chosen as the reference point. Apart from serving as standalone variables to reflect the changes in the constant term, which indicate the effects of time or wave on the outcomes, such dummy variables can also be used to interact with key explanatory variables to examine the changes in the effect of that variable over a certain time or survey period (ibid.). The coefficient of the interaction term is the DD estimate measuring such temporal changes.

For this study, a simple regression model of the relationship between the dependent variable y (i.e., activity-travel time use) and a set of socio-demographic predictors X_{SD} and ICT-usage predictors X_{IU} (i.e., time spent on the Internet) can be initially formulated as Eq. 5 without considering temporal changes:

$$y = \beta_0 + \beta_{SD}^T X_{SD} + \beta_{IU}^T X_{IU} + u \quad (5)$$

where β_{SD}^T and β_{IU}^T is the vector of coefficient estimates for X_{SD} and X_{IU} , respectively while β_0 is the constant term. After pooling the two cross-sections, the 2005/06 SHS ($Y1$) and the 2015 iMCD ($Y2$), a dummy variable ξ_{Y2} was created to indicate whether or not a specific respondent belongs to $Y2$ (the year 2015). In this case, according to the DD settings and particularly considering the temporal dynamics in the relationship between time spent on the Internet and travel behavior, the regression model was re-formulated as below:

$$y = \beta_0 + \beta_{0Y2} \xi_{Y2} + \beta_{SD}^T X_{SD} + \beta_{IU}^T X_{IU} + \beta_{IUY2}^T \xi_{Y2} X_{IU} + u \quad (6)$$

The additional coefficient estimate β_{0Y2} represents the change in constant item observed in $Y2$ (2015) as compared to $Y1$ (2005/06), based on the assumption of common error for the pooled datasets. The coefficient vector β_{IUY2}^T is the DD estimator, which measures the changes in the effects of ICT use on activity-travel behavior (i.e., the outcome variable in the model) over the two survey periods. In this situation, β_{IU}^T captures the differences in activity-travel outcomes between the ICT users (treatment group) and the non-users (control group) in the referenced year ($Y1$).

In order to find an overall trend of changes in the ICT-travel relationship over time, Eq. 5 was initially estimated for each survey year with the application of the aforementioned MDCEV model, which is somewhat equivalent to running the regression with all regressors interacting with the year indicator (Wooldridge 2013). The comparison was made based on the two individual sets of estimates. Pooling cross-sections and the DD estimation were subsequently implemented and integrated with the specified MDCEV model for estimating Eq. 6, capturing the exact DD over time. The MDCEV models were specified and run using the R code from the package “MDCEV Estimation_With Outside Good”, which is provided by the Mobility Analytics Research Group (MARG) (MARG 2016).

Results and findings

The estimation results of the MDCEV models for each of the two survey waves are summarized and presented in Table 3, while Table 4 shows the MDCEV results with the inclusion of the DD estimator for a pooled survey sample. Other activity duration, which is the outside good in our MDCEV model specifications, is considered as the base alternative. To focus on the Internet-travel relationships over time, only the coefficient estimates

Table 3 Results of the MDCEV models for each survey year

Samples	2005/06 SHS-GCV				2015 iMCD			
	Maintenance		Leisure		Maintenance		Leisure	
	Activity duration	Travel time						
Baseline constants	-5.026**	-9.243**	-5.673**	-8.082**	-4.963**	-9.445**	-5.107**	-7.884**
γ parameters	355.629**	160.633**	650.274**	160.819**	388.806**	126.551**	640.290**	177.903**
Socio-demographics								
Age (reference: age 16–34)								
Age 35–55	.042**	.025**	-.066**	-.023**	.064*	.032**	-.048**	-.016*
Age > 55	.035	.006	-.052**	-.036*	.017	-.002	-.061**	-.028**
Gender (female = 1)	.764**	.370**	-.158*	-.064	.821**	.407**	.036	-.028
No. of kids	.252**	.201**	-.436**	-.157*	.189**	.230**	-.389**	-.204**
No. of cars	-.335**	-.127*	.612**	.245**	-.502**	-.185**	.668**	.315*
Driving license (own = 1)	.217**	.079	.320	.067*	.196**	-.114	.159	.046
Personal income	.475**	.327*	.782**	.463**	.390**	.343**	.804**	.278**
Employment (employed = 1)	-.532**	-.284**	-.624**	-.447**	-.621**	-.307**	-.682**	-.229**
Mandatory activity duration	-.086**	-.035*	-.117**	-.069**	-.074**	-.028**	-.085**	-.053**
Residential locations (reference: Urban)								
Town	-.338**	-.087*	.279	-.042	-.426**	-.137**	-.341*	.177
Rural	-.479**	-.260**	-.168	-.149*	-.480**	-.256**	.180	.054
Internet access at home	.170**	-.041	.224	-.130	-.205**	-.079*	-.271**	-.076**
Travel date (weekdays = 1)	-.326**	-.204*	-.378**	-.303**	-.289**	-.250**	-.407**	-.229**
Internet use (reference: Never)								
Up to 1 hr	.110*	.085	.230	.059	.150	.067	.213	.079
1–5 h	.369**	.276**	.119	-.205	.476**	.325**	.179	.220*
5–10 h	.554**	.421**	.321	.079	.287**	.168*	.205	.158

Table 3 (continued)

Samples	2005/06 SHS-GCV			2015 iMCD		
	Maintenance	Leisure	Travel time	Maintenance	Leisure	Travel time
10–20 h	.320**	.345**	.056*	–.366**	–.386**	–.259**
Over 20 h	.062	.136	.125	–.559**	–.547**	–.368**
Sample size	5006			1484		
Log-likelihood	–63,884.152			–18,569.341		

* Statistically significant at the 10% level; ** Significant at the 5% level

Table 4 Results of the MDCEV model with inclusion of the DD estimators

Pooled sample	2005/06 SHS-GCV and 2015 iMCD			
	Maintenance		Leisure	
	Activity duration	Travel time	Activity duration	Travel time
Baseline constants	− 5.045**	− 9.376**	− 5.341**	− 8.106**
γ parameters	346.330**	149.040**	598.758**	157.533**
Wave (Wave 2015 = 1)	− .045	− .110**	− .236**	− .207**
Internet use (reference: Never)				
Up to 1 hr	.079*	.023	.167	.041
1–5 h	.358**	.269**	.124	− .176
5–10 h	.537**	.432**	.260*	.091
10–20 h	.319**	.328**	.275	.044*
Over 20 h	− .006	.057	.077	− .086
Wave*Internet use (reference: Never)				
Year*Up to 1 h	.043	− .022	− .008	− .016
Year*1–5 h	.110	.045	.055	.230
Year*5–10 h	− .259**	− .248**	− .118	.005
Year*10–20 h	− .679**	− .618**	− .569**	− .335**
Year*Over 20 h	− .620**	− .532**	− .626**	− .447**
Sample size	6,490			
Log-likelihood	− 82,606.953			

*Statistically significant at the 10% level

**Significant at the 5% level

of key predictors (Internet use, and survey wave indicator) and their interaction items are presented in Table 4. By comparing the 2005/06 (SHS-GCV sample) and 2015 (iMCD sample) results shown in Table 3, overall stability or variation regarding the relationships between activity-travel behavior and a set of predictors across time can be suggested. By contrast, Table 4 reveals the associations of time indicator and Internet use with individuals' activity-travel time use and the exact temporal changes in the Internet-travel relationships.

Baseline preference and satiation parameter estimates

The first rows of Tables 3 and 4 correspond to the baseline preference constants which capture individuals' general tendencies to undertake each type of outdoor non-mandatory activities and associated trips. It is clear that all the baseline preference constants for the two activity types and related trips are negative in both Table 3 and Table 4, suggesting the overall higher levels of participation in other activities (i.e., base alternative in model specifications). Such a result is unsurprising as all individuals in the samples participated in those other activities to some extent. It is also manifest that for all the three samples (2005/06 SHS-GCV sample, 2015 iMCD sample, and the pooled sample), the baseline parameter estimate for the maintenance activity participation is the largest among the four such parameters, although travel for maintenance purposes has the smallest baseline

constant. This result suggests that undertaking out-of-home maintenance activities has the greatest baseline preference when individuals allocate time for non-mandatory activity and travel purposes, while maintenance-related trips are the least preferred.

The second rows of parameters reported in Tables 3 and 4 correspond to the satiation parameter γ_k estimates. These parameters indicate the differences in the satiation effects (along with allowing for corner solutions or zero durations) among the two activity types and related trips, with a larger value suggesting a lower satiation effect and potentially longer duration. Clearly, compared to other types of activities/trips, out-of-home leisure activities has the highest γ_k value for all the three samples, implying that individuals are the least likely to satiate in undertaking leisure activities and are willing to spend more time on them. The opposite situation is seen for maintenance-related travel, which has the lowest γ_k value.

Relationships between socio-demographics and activity-travel time use over time

The subsequent rows of coefficient parameters in Tables 3 and 4 correspond to the associations between individual and household-level variables and baseline preferences for activity participation and trips. According to Table 3, the correlations between socio-demographics and activity-travel patterns for both maintenance and leisure purposes have remained relatively stable over the ten-year period. For instance, compared to young people, both the middle-aged people (aged between 35 and 55 years) and the old people (aged over 55) show a higher propensity to perform leisure-related activities and trips in both survey periods. While physical issues might limit the elderly participating in outdoor leisure activities, greater attention to work and family might discourage the middle-aged group from undertaking such activities. In addition, the middle-aged group has a greater propensity to undertake out-of-home maintenance activities and associated travel than the young group, which may result from the greater needs of the middle-aged group to perform the maintenance tasks for their families. In comparison to males, females are generally more inclined to invest time in outdoor maintenance tasks in both years, which reflects the traditional gender roles in taking responsibility for such tasks.

Additionally, the number of children in households is positively related to adults' propensities to perform maintenance activities and associated travel and negatively related to their preferences for leisure-related activities. Since more time is dedicated to childcare, which is likely to be seen as extra maintenance activities (e.g., escorting children to/from schools and extra shopping for children), adults in those households may have less time for recreation. In contrast, in both 2005/06 and 2015, people from households with more vehicles are less inclined to engage in out-of-home maintenance activities, but more likely to undertake leisure pursuits. However, people who have valid drivers' licenses show a greater propensity than those without a license to undertake maintenance tasks.

In both time periods, people with higher incomes are generally more inclined to spend time participating in activities and trips for non-mandatory purposes, suggesting that more affluent families are more capable of affording these activities. In terms of employment status, compared to unemployed people, the employed in both survey periods are less likely to participate in both maintenance- and leisure-related activities and travel. Such a negative correlation is also seen between the duration of undertaking subsistence activities and the propensity to engage in non-mandatory activities and make associated trips.

In addition, compared to urban residents, people living in smaller towns and rural areas show a lower inclination toward activity engagement and trips for maintenance purposes.

As commercial and retail facilities like shops and banks may not be in close proximity and hence are not easily accessed by those living in more remote locations, there may be fewer opportunities to undertake maintenance activities on a daily basis. Although individuals who have Internet access at home have a higher propensity to pursue outdoor maintenance activities in 2005/06, they are less likely to perform activities for both maintenance and leisure purposes and associated trips in the later year of 2015, compared to those who do not have access to the Internet at home. As people have been able to undertake increasing activities online (for non-work purposes) at home more recently, they might reduce their out-of-home activity participation for non-mandatory purposes. As for the correlations between travel date and activity-travel time use, people are generally more inclined to perform out-of-home activities and associated travel for non-mandatory purposes on weekends than on weekdays, which is consistent with the findings of previous studies (Bhat and Misra 1999; Ho and Mulley 2013; Raux et al. 2016).

Relationships between Internet use and activity-travel time use over time

The MDCEV results summarized in Table 3 also imply that there are differences over the ten-year period in the relationships between the levels of Internet use and the propensity to undertake maintenance and leisure activities and travel to those activities. In 2005/06, compared to those never using the Internet for personal purposes, Internet users (in the GCV region) are generally more likely to perform out-of-home activities and trips for maintenance purposes. This complementary association peaked at the five-to-ten-hours usage level, indicating that up to a moderate level of time spent on the Internet, individuals' propensities to participate in maintenance activities and travel to perform those activities, as well as time spent on those activities and trips, increased in 2005/2006.

However, for those spending over 20 h per week on the Internet, the complementary association is no longer significant. This is possibly due to the time budget effect, indicating that people do not have time to do more maintenance activities or related travel if they spend a large amount of time on the Internet as they need to engage in work, sleep, and other mandatory, as well as leisure activities.

We do not find evidence of a significant association between the extent of Internet use and level of preference for undertaking leisure activities and associated travel in 2005/06. This means that time spent on the Internet for personal purposes, overall, has little or minor influence on people's propensities to pursue leisure-related activities outdoors in the first of the two periods that we considered.

We find that the landscape of Internet use and non-mandatory activities and associated travel changes between 2005/06 and 2015. In 2015, a low to moderate level of Internet usage (up to ten hours per week) is still positively related to individuals' level of preference for maintenance-related activities and travel. However, heavy users who spend over ten hours on the Internet are less likely to invest time to undertake maintenance-related activities and related travel. This is indicative of an increasing substitution association—that over time, those who use the Internet heavily are spending less time on, for example, shopping and retail activities and travel to those destinations. One explanation for this Internet–travel association is that people are increasingly performing many of their maintenance activities, such as shopping and banking, at-home and online, in comparison to 2005/06, and are not bound by daily time budget constraints. Such a substitution association is also detected for heavy Internet users in 2015 regarding their leisure-oriented activity-travel behavior, indicating a potential increase in at-home and online leisure activities

and a decline in out-of-home leisure activities and physical travel to those activities for such heavy Internet users.

Based on these findings, the relationship between time spent using the Internet, and the time spent on non-mandatory activities and associated travel, has evolved over time. For heavy users of the Internet, this temporal evolution implies a transition from complementarity (for maintenance purposes) or neutrality (for leisure purposes) to substitution. Again, this could be due to the time constraints and the growing availability of Internet solutions allowing maintenance and leisure activities to be carried out via the web as well as increasing levels of digital literacy among consumers comfortable with participation and making transactions, thereby requiring lesser out-of-home travel. Additionally, as people spend more hours online, only limited time is available for them to perform other out-of-home activities.

The DD approach was applied to verify the results of the above trend analysis and to quantify the changes in the Internet–travel associations further. The results and findings are discussed as follows.

Quantified changes in the relationships between internet use and activity-travel time use over time

Table 4 presents the coefficient estimates of key predictors (survey wave indicator, Internet use, and their interaction items) on activity-travel time use for a pooled sample across time. According to the results, the wave indicator, where the 2005/06 sample (*Y1*) was treated as the reference, generally has negative correlations with individuals' propensities to perform out-of-home activities and trips, especially for leisure purposes. It suggests that people are less inclined to undertake travel for maintenance purposes and outdoor leisure activities over time.

The coefficients in terms of Internet use displayed in the table reflect the Internet–travel relationships in the referenced year (2005/06). Similar to the findings for the 2005/06 sample alone, the use of the Internet is, in general, positively correlated with individuals' inclinations towards activity participation and trips for maintenance purposes, but has little correlation with their leisure-related mobility.

As for the key interest of this study, the temporal changes in the effects of Internet usage are captured and quantified by the coefficients of wave-Internet interaction items, namely, the DD estimators. It is clear that the interaction items are significantly and negatively correlated with individuals' maintenance-related mobility behaviors only for those Internet users spending over five hours online per week. Since the complementary associations between Internet use and maintenance activity participation as well as related trips have been generally detected for those users in 2005/06, the negativity of coefficients implies that, at the same usage levels, the use of the Internet in 2015 tends to generate less, or even substitute, physical activity undertaking and trips for maintenance purposes. In fact, when the changes are added to the initial Internet-induced effects in 2005/06, the substitution relationship is found among the heavy users with over-ten-hours' usage in 2015. This result is consistent with the findings of the previous trend analysis. However, for the light Internet users, who spend no more than five hours online, the DD estimators are not significantly correlated with the activity-travel variables, which means the Internet–travel relationships regarding maintenance purposes do not change significantly among the light users over the ten-year period. Likewise, temporal changes in the interaction between Internet use and mobility behavior for leisure purposes are only found to be significant for heavy Internet

users, and the changes are negative. As the associations between Internet use and leisure-related activities and trips are found to be neutral in 2005/06, they would become substitutive for the heavy users in 2015 after considering such changes, which is, again, in line with the results of trend analysis.

Overall, these findings reveal that Internet–travel relationships, in terms of both maintenance and leisure activity purposes, change over time, and such changes are generally negative, leading to a trend of more substitutive and less complementary associations. Such temporal changes are significant only for the medium-to-heavy Internet users who spent over five hours online per week.

Summary and conclusions

This study empirically investigates the temporal changes in the relationships between the time spent on the Internet and activity–travel behavior in terms of non-mandatory activity purposes (i.e., maintenance and leisure activity purposes). In order to achieve a (quasi)longitudinal analysis, this study overcomes data and information deficiency by using datasets from two major cross-sectional surveys implemented in Scotland, the 2005/06 SHS and the 2015 iMCD Survey, which were similarly designed and structured. To accommodate the multiple discreteness characterizing activity–travel choice and duration, the MDCEV model, which allows the discrete and continuous choice of multiple alternatives at the same time, was applied to examine the effects of Internet use on activity–travel time use in both 2005/06 and 2015. Additionally, the DD approach was integrated with the MDCEV method to capture and quantify the exact changes in the Internet–travel relationships further over the ten-year period.

Both the trend analysis and the DD analysis in this study suggest that the relationships between the time spent on the Internet and activity–travel time use for non-mandatory purposes have changed during the period between 2005/06 and 2015, and these changes are generally in a negative trend. More specifically, they tend to breed a new ICT–travel interaction of substitution, rather than complementarity (for maintenance purposes) or neutrality (for leisure purposes) in relationships that were found at the earlier point (2005/06). It seems that ICT is more likely to play a discouraging—rather than a facilitating—role in influencing people’s engagement in physical activities and travel, as a result of technological evolution over time. However, such changes are only significantly detected for medium-to-heavy Internet users who spend over five hours online per week. For light users, temporal changes in the ICT–travel relationships are not significant for either maintenance or leisure non-mandatory activity purposes. This phenomenon is not surprising since the increasing application of ICT in all aspects of daily life (e.g., teleshopping, telemedicine, and e-banking), which is brought about by technological evolution over time, enables and stimulates people to replace physical activities with virtual ones, particularly for those heavy ICT users dedicating a large share of their daily time budget to the Internet.

The above findings suggest that people are increasingly inclined to adopt a sedentary lifestyle by substituting out-of-home activity participation and travel with virtual activities. From a long-term perspective, such sedentary lifestyles may result in some health issues (e.g., obesity), especially for those showing high reliance on ICT in their daily life, such as the millennial generation which is dubbed as the “go-nowhere” generation (Buchholz and Buchholz 2012). In addition, as ICT is increasingly and rapidly penetrating all types of business services, such sedentary lifestyles imply an increasing challenge posed

by the online businesses providing maintenance and leisure services to the traditional (offline) business services of the same kind. Under these circumstances, although some personal travel demands may seem to be reduced, the foreseeable growth in logistics due to the increasing prevalence of e-commerce (e.g., online shopping and food ordering online) would still bring about many transportation-related issues such as increased congestion, pollution, and accidents.

Further exploration based on this study could be made by considering more specific usage of ICT and its dynamic effects on activity-travel behavior over time. Since ICT is pervading people's daily lives ever further, the diversity of the ICT-travel interactions and the temporal dynamics in such interactions would be further revealed if ICT uses were specified in the model on a daily basis or in terms of, for example, purpose of usage (e.g., maintenance and leisure purposes), method of access (e.g., personal computers, laptops, and mobile phones), and place of access (e.g., home, workplace, and school). In addition, another direction which could be pursued in the future is to examine the spatial changes in ICT-travel relationships across urban and rural areas because people living in urban or rural areas may have different ICT use behaviors partly due to their different education levels and accesses to the Internet (i.e., the digital divide).

Author contributions Guoqiang Wu made substantial contributions to the conception and design of this paper, as well as analysis and interpretation of data, and drafted the manuscript. Jinhyun Hong and Piyushimita Thakuriah revised the initial draft critically for important intellectual content. Besides, Jinhyun Hong contributed to the design of the paper structure and the selection of modeling techniques. All authors approved this version to be considered for publication, and agreed to be accountable for all aspects of this work in ensuring that questions related to the accuracy and integrity of any part of the work were appropriately investigated and resolved.

Code availability Models were developed and run in *R*.

Compliance with ethical standards

Conflicts of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of data and material The Scottish Household Survey (SHS) data used in this study were accessed through the UK Data Service, the Integrated Multimedia City Data (iMCD) were accessed through the Urban Big Data Centre, University of Glasgow. Both accesses were under the UK's academic licenses.

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Guoqiang Wu is a Research Fellow in Leeds Institute for Data Analytics which is based at School of Geography, University of Leeds. His research centers on large-scale data and behavior modeling; smart cities and urban mobility; social and urban informatics; spatial and policy microsimulation. He usually works with individual-based or micro-level models and big data analytics to predict and simulate individuals' behavior and demands. He is currently a core researcher in the consortium of Systems Science in Public Health and Health Economics Research (SIPHER) funded by the UK Prevention Research Partnership (UKPRP). He previously worked and studied at the Urban Big Data Centre (UBDC) in the University of Glasgow where he received his PhD in 2018.

Jinhyun Hong is a Senior Lecturer in Transportation Planning at the University of Glasgow, and leading the Urban Big Data Centre's Transport and Infrastructure research. His research focuses on the interactions among built environment, travel behavior and air quality; information and communications technologies (ICT), transport and places; built environment, safety and walking. He received his PhD in Urban Design and Planning department at the University of Washington, Seattle, USA in 2013. Before coming to Glasgow, he worked as a research assistant and staff at the University of Washington and was involved in several projects related to travel behavior including vehicle miles travelled and other non-motorized travel activities such as walking and cycling.

Piyushimita Thakuriah is Dean of the Bloustein School of Planning and Public Policy in Rutgers University, Distinguished Professor of Transportation and Urban Informatics, and Director of the Rutgers Urban and Civic Informatics Lab. Her research has been funded by the world's leading scientific research sponsors including the US National Science Foundation, European Commission, and UK Research and Innovation, and she has delivered keynote addresses and plenaries in leading venues such as US National Academy of Sciences, European Commission in Brussels and Luxembourg, Royal Academy of Engineering in London, Leibnitz Center for Informatics in Germany, and National Institute of Informatics in Japan. Her research interests are in transportation planning and operations; big data and social and economic cyberinfrastructure; and smart cities and urban informatics.

Authors and Affiliations

Guoqiang Wu¹  · Jinhyun Hong² · Piyushimita Thakuriah³

Jinhyun Hong
Jinhyun.Hong@glasgow.ac.uk

Piyushimita Thakuriah
p.thakuriah@rutgers.edu

¹ School of Geography, University of Leeds, Woodhouse Lane, Leeds LS2 9JT, UK

² Urban Big Data Centre, University of Glasgow, 7 Lilybank Gardens, Glasgow G12 8RZ, UK

³ Edward J Bloustein School of Planning and Public Policy, Rutgers University, 33 Livingston Ave., New Brunswick, NJ 08901, USA