Using Virtual Accessibility and Physical Accessibility as Joint Predictors of Activity-Travel Behavior

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ABSTRACT

In this study, we propose a conceptual and analytic framework anchored on the concepts of physical and virtual accessibility (the "ease" with which opportunities or activities can be reached in the physical and in the virtual space, respectively) to investigate the rich interplay between virtual and physical activity engagements in multiple activity purposes, while controlling for information and communication technology (ICT) use measures, physical accessibility measures, and demographics. Our framework considers that activity-travel choices are consequences of individual, household, and work characteristics that are mediated by virtual accessibility and physical accessibility. As part of our analysis, we also analyze activity chaining characteristics during travel to study any fragmentation impacts caused by ICT use on activity engagement and scheduling. We use data from the 2011 and 2012 National Travel Survey in Great Britain and apply Bhat's (2015) generalized heterogeneous data model (GHDM) to jointly model multiple activity and travel outcomes. Our results provide important insights for social welfare, work-life balance, and equity policies, and suggest that decisions regarding virtual activity participations and in-person out-of-home activity participations are determined as a package. Ignoring this package nature of choices can lead to misleading inferences about the effects of virtual activity participations on in-person out-of-home activity participations.

Keywords: ICT use, virtual/physical activity participation, GHMD model, time poverty, social exclusion, social roles.

1. INTRODUCTION

As information and communication technologies (ICTs) become more popular, and the digital world permeates into our everyday lives, the divide between the virtual and physical worlds begins to blur as we make continuous and joint decisions about which activities we can, need, and want to perform in person or virtually. Because of the interdependency across choices associated with different types of activities in one's schedule (due to, for example, time allocation, geography, trip chaining, and joint participation), it is expected that the opportunity to conduct an activity virtually or, at the other extreme, the lack of opportunity to access an activity physically, will affect the overall activity planning of the individual. Thus, although approaches that analyze isolated interactions between specific single types of tele-activity and their immediate location-based counterparts (for example, online shopping versus in-store shopping) can potentially provide important insights on immediate substitution and complementarity patterns, they are limited in their ability to guide future transportation and land use planning.[1]

In this study, we propose a comprehensive modeling framework, anchored on the concepts of virtual and physical accessibility (the "ease" with which opportunities or activities can be reached in the virtual space and in the physical space, respectively), to examine and capture interactions in activity-travel choices associated with both virtual and physical participations and for multiple activity purposes at the same time (in this paper, the term "physical activity participation" implies out-of-home (OH) activity participations undertaken in physical presence, as opposed to virtually). In particular, we define virtual accessibility and physical accessibility as two major latent constructs that mediate individuals' activity engagement decisions (both virtually and physically).

A significant amount of the empirical work investigating the relationship between ICT use (that is, virtual activity behavior) and physical activity-travel behavior is based on the typology developed by Salomon (1986) and built upon by other researchers (Couclelis, 2000; Hubers et al., 2015; Kenyon and Lyons, 2007; Berliner et al., 2015) that establishes six main impacts of virtual activities on personal physical activities and travel: substitution (replacement of a location-based activity by a tele-activity, thus eliminating travel), complementarity (a virtual

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[1] Similar to Pawlak et al. (2015), we consider tele-activities as those activities that traditionally involve travel but can be conducted remotely by means of ICT (e.g., telecommuting). On the other hand, virtual activities encompass a broader range of activities in the digital world, including tele-activities but also other activities such as microblogging and social media use (such as Twitter and Facebook) that have no corresponding physical location "twin".

activity leads to new location-based activities), modification (virtual activity changes the timing, duration or place of a location-based activity), neutrality (there is no observed effect of the virtual activity on location-based activities), activity fragmentation (splitting of a certain activity into several smaller pieces that can be performed at different times and locations, because ICT allows remote and continuous access to files, information, and people), and multitasking (the simultaneous realization of two or more activities during the same time period, such as teleworking or shopping online while traveling as a passenger or even physically shopping at the same time; in our empirical analysis later, we are unable to consider multitasking due to data limitations). These "six effects" impacts have generally been studied by examining specific tele-activities and their direct location-based counterparts such as, for example, telecommuting and commuting (see, for example, Zhu, 2012; Hu and He, 2016) or online shopping and in-store shopping (see, for example, Ding and Lu, 2017; Lee et al., 2017). But, while analyses that focus on a single activity purpose can provide useful insights to understand general tendencies of behavioral patterns, they underestimate the true potential that virtual activities may have in re-shaping individuals' schedules and activity-travel choices. Thus, the few studies in the literature that have taken a more comprehensive multi-activity purpose approach (see Wang and Law, 2007; Ren and Kwan, 2009; Lila and Anjaneyulu, 2016) underscore the intricate and complex nature of the interactions between the digital and the physical world. For example, as suggested by some of these studies, the combination of online shopping and in-store shopping can increase the overall efficiency of shopping activities and reduce the overall time spent shopping, which in turn can increase the frequency and/or time spent in physical discretionary activities. At the same time, as some of these multiple activity purpose studies suggest, in examining the impacts of an increasingly ICT-driven world, it is also important to consider physical activity accessibility in the form of physical built environment (BE) variables.

To summarize, there is a need to jointly examine the different types of virtual activities with physical activity-travel characteristics, and to consider multiple types of activities of an individual's everyday life in a single comprehensive framework. Most importantly, we believe that the earlier literature that uses the "six-effects" framework of virtual activity effects on physical activity-travel behavior is seriously limiting, as it is applied, in the sense that it implicitly assumes that decisions regarding virtual activities are determined first, which then impact decisions on physical activity engagement. That is, there is the assumption in the

literature that virtual activity participation is exogenous to physical activity participation decisions when examining the "six-effects". Our viewpoint, on the other hand, models virtual and physical activity participations as a joint package decision, thus alleviating endogeneity bias issues in the interactions between virtual activities and physical activity engagement. As we will show later in our empirical analysis, these endogeneity bias considerations can be substantial. In fact, our results suggest that virtual accessibility measures (or VAMs) and physical accessibility measures (or PAMs or BE measures) jointly (and simultaneously) affect virtual activity engagement (VAG) and physical activity engagement (PAG), with relatively little remnant impacts of virtual activity engagements themselves on physical activity engagements in the way the literature has characterized the "six effects". The next section discusses the concept of virtual accessibility in some detail (as a complement to the more often-used concept of physical accessibility).

1.1 The Virtual Accessibility Concept

Kenyon et al. (2003) and Kenyon (2010) define virtual accessibility as the "Internet enabled accessibility [that] provides an alternative to reaching opportunities, goods, services, and social networks, providing access without physical travel . . . [it] acts to substitute for physical mobility. . . It can also act to supplement for [physical] accessibility where previously there was a deficit."[2] Virtual accessibility can represent more than access without travel; it can also characterize the enhancement of the travel experience and physical accessibility by the use of real-time information provided by ICT use (van Wee et al., 2013; Lu et al., 2014). The use of this concept allows a parallel with physical accessibility and can also incorporate constraints and behavioral aspects associated with ICT adoption and use. We posit that the level of virtual accessibility that one may experience should depend on at least five aspects: (1) the ownership of an ICT device, (2) the subscription to a network provider (can refer both to Internet and calls) and the coverage of such a network, (3) the ability (or knowledge) to use the gadget and available functionalities (also known as technology-savviness), (4) the ability to conduct activities virtually (for example, if the individual's job requires physical presence at the work place, then his/her virtual accessibility is immediately limited, at least as related to the work

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[2] Kenyon uses the terms "virtual mobility" and "virtual accessibility" interchangeably to refer to the same concept. Matous (2017) uses the term "virtual mobility" with the same meaning as Kenyon, while van Wee (2015) uses the term "ICT-based accessibility."

activity purpose), and (5) the overall time available to the person to pursue specific types of activities (for example, time available after work to pursue shopping or leisure). Considering such abilities and constraints to virtual accessibility is fundamental to understanding the potential impacts of ICT, since it is well known that there is a large gap between technology development, technology adoption, and technology impacts on behavior. As discussed earlier, starting with the concept of virtual accessibility (formed on the basis of perceptions of virtual accessibility measures or VAMs), and its interaction with physical accessibility (formed on the basis of perceptions of physical accessibility measures or PAMs), has the advantage of appropriately recognizing the trade-offs and rich interplay in the decisions that simultaneously drive virtual activity engagement (VAG) and physical activity engagement (VAG) in multiple activity purposes, while controlling for VAMs, PAMs, and demographics.

1.2. Virtual and Physical Accessibility as (Latent) Perceptions

In this paper, the virtual and physical accessibility "mediators" are considered as latent constructs that represent the subjective perceptions of each individual, based on (and impacted by) VAMs and PAMs, respectively. Accessibility can be broadly defined as the ease with which opportunities or activities can be "reached". It is a multidimensional concept and a result of the interaction among multiple factors, including the needs and abilities of the individual depending on such characteristics as age, income, educational level, and household context (Geurs and van Wee, 2004). Although the literature presents an extensive list of possible PAMs (see Páez et al., 2012, for a review), simply focusing on objective measurements of the built environment, transportation system, and even temporal constraints (associated with business hours, for example) may not be adequate. Individuals living in very similar locations may have distinct and different perceptions of physical accessibility due to differences in time budgets and space–time restrictions resulting from engagement in fixed activities, or even due to differences in perceptions associated with personalities, societal roles, and lifestyles. Indeed, Curl et al. (2011) conducted semi-structured interviews with Local Transport Authorities (LTA) in England and concluded that the measures of accessibility often used by planners may not capture the complex social interactions, perceptions, and behaviors that influence travel. A number of respondents suggested that a good measure of accessibility would incorporate how people psychologically

perceive accessibility. A similar case may be made about the importance of considering intrinsic perceptions in forming a good measure of virtual accessibility.

Similar to other psychological constructs, however, there is not a single or specific measure to quantify perceived accessibility. Therefore, it is appropriate to consider that perceived accessibility is an underlying latent (to the analyst) factor that gets manifested in the form of multiple expressed indicators. This latent variable may have a structural relationship with (be explained by) individual characteristics and objective accessibility measures, and also have a stochastic component to account for individual-perceived and analyst measurement errors. This notion of a latent construct for accessibility and modeling approach is applicable to both virtual and physical accessibility, and if both types of accessibility are used in the same model, the relationship between the two stochastic types of accessibility can be quantified by the correlation between the two latent constructs. Further, the presence of individual-specific stochasticity in these latent constructs, and the impact of these latent constructs on VAG (such as working from home, and shopping for food/other goods on-line) as well as PAG (such as participation and duration in OH mandatory, maintenance, and discretionary activity episodes) immediately implies jointness (unobserved correlation) in decision outcomes across VAG and PAG behaviors. Such a framework also enables us to capture any additional recursive impacts among the VAG and PAG behaviors, <u>after</u> accounting for the jointness among these behaviors.

2. Data Source and Analysis Framework

The 2011 and 2012 National Travel Survey in Great Britain collected detailed information on socio-economic and demographic characteristics of households and individuals. It also asked every individual in the household to maintain a seven-day travel diary. Details of the data set and survey administration are available in the technical report (Taylor et al., 2013). For the current analysis, we selected the individual in the household who was both a worker (full-time and part-time) and the main person responsible for food shopping (for reasons that we make clear in the next paragraph). The final sample in our analysis comprises 3319 workers.

The outcomes related to virtual activity engagement (VAG) collected in the survey pertained to the frequency of working from home, whether the household's main method of food shopping was online and/or by phone, and the frequency of food and goods purchased online or by phone (and delivered to the house). The frequency variables, however, are not actual count

variables, but are collected in ordinal categories. For example, the frequency of food purchased online/by phone and delivered to the house (which we will simply refer to as the "frequency of food deliveries" from here on, and similarly we will refer to the frequency of goods purchased online or by phone and delivered to the house as the "frequency of goods deliveries") is collected in four ordinal categories: less than once a year, less than once a month, less than once a week, and one or more times per week. Since the VAG outcomes are focused primarily on food purchases, we decided to focus our analysis on the individual in the household who is the main responsible person for food shopping for the household (unfortunately, our data did not elicit information on virtual discretionary activities such as online socialization and recreation, and so we are unable to consider such virtual activities in our empirical analysis; however, our conceptual framework may be extended in a straightforward fashion to include virtual discretionary activity engagement if data were available).

The virtual accessibility measures (VAMs) impacting virtual activity engagement (VAG) frequency (as well as physical activity engagement (PAG) characteristics to be discussed later) in our analysis include (a) occupation type (managerial/professional jobs relative to other occupation types as a binary variable) that may play a role in determining virtual accessibility, and (b) internet availability within the home (a binary variable). While additional information related to ICT ownership such as the availability of laptop computers and smartphones (to capture availability effects), subscription to/coverage of a network provider (to capture "range" effects of virtual reach), and knowledge/comfort levels with technology use (to capture technology-savviness effects) would have been ideal VAMs, these were not collected in the survey.

In terms of physical activity engagement (PAG), we computed the number of OH weekly activity episodes (a count variable) and the average OH activity episode duration (grouped in ordinal categories, as discussed later) in each of the mandatory, maintenance, and discretionary activity purposes (the mapping of the disaggregate activity purposes collected in the survey into the three broad activity purposes just mentioned is available from the authors). The reason for our focus on average activity episode duration, in addition to the count of weekly activity episodes, is to examine potential activity fragmentation (as defined in the literature) due to VAG. Within the category of PAG, we also considered household vehicle availability (represented as an ordinal variable based on the ratio of the number of vehicles to the number of adults in the

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household). While not an activity engagement variable per se, it represents a closely related travel-related variable that can be impacted by the latent accessibility constructs. Further, there is reason to believe that vehicle availability and PAG patterns are jointly decided on as a package, which implies that vehicle availability needs to be treated an endogenous variable and not exogenous. Finally, to characterize activity modification/scheduling in physical activity engagement, we also computed the average number of trips per tour over the seven days of the week (averages are expressed in four ordinal categories) and the average distance across all trips undertaken between successive pairs of activity episodes in a tour (that is, the average trip distance per tour, which is modeled as continuous variable with a natural logarithm parametrization). A tour in our paper is defined as a home-based tour (a sojourn starting and ending at home).

The physical accessibility measures (including BE measures, or more generally PAMs) impacting (virtual and physical) activity engagement frequency characteristics included respondent-provided non-auto (walk/transit) travel times from their homes to the closest railway station, hospital, and shopping center. The study also collected travel times to other services such as general practitioner, chemist, grocery, and post office. However, the vast majority of the sample have access to these services within very close proximity, contributing little to heterogeneity across individuals in these measures. Therefore, only travel time to the closest railway station, hospital, and shopping center are used in the model.

Finally, the data also allowed us to use indicators for the physical accessibility latent construct. To be clear, the VAG and PAG variables discussed earlier also are effectively indicators of the virtual and physical accessibility latent constructs, but we will characterize these activity engagement variables as outcomes in this paper (because these outcomes are of primary interest as the endogenous variables in our analytic framework). In terms of the indicators of the physical accessibility latent construct, the data provided information on the following four respondent-provided perception variables: (a) ease of commute without a car, (b) ease of shopping without car, (c) quality of bicycle lanes in the vicinity of the respondent's residence, and (d) quality of roadway pavement in the vicinity of the respondent's residence. All of these were collected in ordinal categories.

The entire analytic framework is presented in Figure 1. The virtual accessibility measures (VAMs), physical accessibility measures (PAMs), and socio-demographics (age, gender,

presence of children in the household, housing type and tenure status, full-time or part-time employment, and household income) impact the virtual accessibility latent stochastic construct (VALSC) and the physical accessibility latent stochastic construct (PALSC) (these are encapsulated by ovals to identify them as being latent constructs). The double headed arrow between the VALSC and PALSC represents correlation effects across the unobserved components of the two latent constructs. The identification of the PALSC is facilitated by the four indicators just discussed in the previous paragraph. The VALSC and PALSC, in turn, and along with the VAM, PAM, and socio-demographics, impact the virtual activity engagement (VAG) and physical activity engagement (PAG) patterns. Finally, we test endogenous effects between (and within) the VAG and PAG outcome variables after controlling for common unobserved effects (through the VALSC and PALSC). These endogenous effects must be strictly recursive for identification and logical consistency reasons (see Bhat, 2015). We represent this by arrows in each direction between VAG and PAG in Figure 1. The extant literature *a priori* assumes that the directionality of the "six-effects" is from VAG to PAG, without considering that the VAG and PAG outcomes may be jointly determined as a package choice, as we do.

The proposed model for the VAG and PAG outcomes is a classic fit within Bhat's (2015) GHDM framework that enables the consideration of the different types of PAG and VAG outcome variables within a joint system. The GHDM has two components joined together. The first component, which is the latent structural equation model (SEM), specifies the relationship, in our empirical context, between the VAMs, PAMs, and socio-demographic characteristics on the one hand and the VALSC and PALSC on the other (the left block to the middle block of Figure 1). The second component, which is the latent measurement equation model (MEM), relates the VALSC and the PALSC to its measurement indicators (the PALSC indicators) and the VAG and PAG endogenous outcomes (the middle block to the right block of Figure 1; the endogenous outcomes include continuous, ordinal, and count variables). Because of the stochasticity in the VALSC and PALSC latent constructs, which influence the VAG and PAG endogenous outcomes, there is a parsimonious unobserved dependence structure among all endogenous variables. Due to space considerations, we will not dwell on the model econometrics and estimation of the GHDM model but refer the reader to Bhat (2015).

2.1. Sample Description

To conserve on space, we present only the statistics associated with the VAG and PAG endogenous outcomes in this paper. The statistics related to the VAM, PAM, socio-demographics, and the four indicators of the PALSC are available in an online supplement at http://www.caee.utexas.edu/prof/bhat/ABSTRACTS/Accessibility/OnlineSupplement.pdf.

Table 1 provides the descriptive statistics on the VAG and PAG outcome variables. The first variable under the VAG category is the frequency of working at home. Even though the majority of the people telecommute only twice a year or less, there is still 7.3% of the sample that telecommutes weekly. With respect to food-purchasing behavior, for a vast majority (93.1%) of individuals, the main purchase channel for food is to travel to the grocery store rather than do so online. This is also reflected in the distribution of the frequency of food delivery, with two-thirds of respondents purchasing food online and having it delivered to their respective homes less often than twice a year. Yet, 8.8% of respondents have food delivered to their house one or more times per week. Individuals have goods delivered more often than food, with 27.8 percent of respondents having goods delivered one or more times per week.

Among the PAG outcome variables (the lower row panel of Table 1), the mean number of mandatory activity episodes per week is 3.9, which is reasonable given the level of telecommuting as well as individuals not working at all on some days of the week (due to vacation, illness, or other personal considerations; almost one fifth of the individuals did not undertake any OH work activity in the survey week). On average, the number of maintenance activity and discretionary activity episodes pursued during the survey week is 2.1 and 3.0, respectively, well below the number of mandatory activity episodes. In terms of average activity duration (in ordinal categories as shown in Table 1), about half of all work episodes are more than 6 hours, while most maintenance episodes take less than 2 hours. A fourth of the sample did not pursue any discretionary activity, but most who did, spent less than 3 hours per episode. Trip chaining is quite prevalent, as only 32% of individuals have an average of two trips per tour. The average trip distance in a tour is 9.3 kilometers. Lastly, the majority of the households has motorized vehicles, but usually no more than one per adult.

3. RESULTS AND DISCUSSION

The final variable specification was obtained based on a systematic process of eliminating statistically insignificant variables, supplemented with a healthy dose of judgment and results from earlier studies. However, within this context, we examined a host of different functional forms for variables, variable specifications, and directionalities of possible recursive effects among the many VAG and PAG outcomes, and obtained the specification that provided the best statistical fit, based on the non-nested model comparison measures discussed in Bhat (2015). In some cases, we left a variable in the specification even if it had only a marginally significant statistical effect, because of the intuitiveness of the effect of the variable and its potential to guide future research.

3.1 Relationship between Exogenous Variables and the Latent Accessibility Constructs

The results of the structural equation component of the model that relates the two latent accessibility constructs of VALSC and PALSC as a function of demographic attributes is presented in Table 2 and discussed below.

3.1.1 Virtual Accessibility Latent Stochastic Construct (VALSC)

The results in Table 2 suggest that individuals aged fifty or over have lower levels of virtual accessibility compared to younger individuals. While younger individuals (millennials, for example) grew up in an era of ubiquitous ICT availability, baby boomers had to adapt to such technological changes in adulthood. As pointed by Helsper and Eynon (2010), older individuals can learn to use digital devices as proficiently as younger individuals; however, it requires a greater effort, which can decrease the perception of access to opportunities in the virtual environment. In that sense, the results also show that higher levels of education have a positive impact on virtual accessibility. Higher household income (relative to a lower household income) is also associated with a higher virtual accessibility, presumably because wealthier people can afford a larger number of technological devices and are usually the first individuals to have access to new technologies that are typically more expensive when first released. Indeed, multiple studies find similar associations between age, education, and income levels and technology use or technology-savviness (see, for example, Lavieri et al., 2017a and Liu and Yu, 2017).

Finally, the two variables representing the exogenous virtual accessibility measures (VAMs) also have the expected effects. Workers pursuing managerial/professional jobs have a higher VALSC than those holding routine, manual and intermediate jobs. That workers in the former occupations tend to have more work flexibility than those in the latter is a finding well established in the literature (Singh et al., 2013). This flexibilization of the work activity for individuals in the managerial/professional profession may be associated with an enhanced potential for re-arrangement of other activities, thereby leading to a higher virtual accessibility level. The absence of internet connectivity in the household, as expected, reduces the individual's virtual accessibility, since the lack of connectivity is a direct constraint to accessing the digital world (Yu and Shaw, 2008; Tranos et al., 2013).

3.1.2 Physical Accessibility Latent Stochastic Construct (PALSC)

As discussed earlier, the indicators used for PALSC correspond to the ease of commuting and shopping without a car, along with the quality of bicycle lanes and roadway pavement in the vicinity of the respondent's residence. As such, therefore, the PALSC in this study will be more reflective of an individual's perception of physical accessibility to opportunities by non-auto modes of travel.

Table 2 indicates that, as expected, variables associated with residential location are the main predictors of PALSC. Living in a townhome or in an apartment/flat is associated with higher urban densities around one's residence, and is therefore naturally associated with a higher perception of physical accessibility than when living in a detached or semi-detached single family housing unit. For similar reasons, renting a residence, rather than owning a residence, is also associated with an increase in PALSC. Living in a metropolitan area, compared to living outside a metropolitan area, also positively contributes to the individual's perception of physical accessibility. Finally, the location-based measures (PAMs) indicate the expected negative effect of travel time (to important activity opportunity locations) on PALSC.

3.1.3 Correlation

The correlation between VALSC and PALSC is considered in our paper to accommodate the possible presence of common unobserved variables impacting VALSC and PALSC. We observe a moderate (but highly statistically significant) positive correlation between the two accessibility

constructs, suggesting that unobserved factors contribute to a simultaneous increase (or decrease) of the perception of both types of accessibility. For example, the individual's degree of self-efficacy, that is, her/his personal judgment of own ability to deal with prospective situations (as defined by Bandura, 1982) is likely to have a similar influence on the perception of both types of accessibility. Further, individuals who are adventurous and exploration-oriented may have a higher VALSC and PALSC than their otherwise observationally equivalent peers (generating the positive correlation). In addition, as discussed in Section 1.1, the ability to use ICT while traveling and the access to real time information may not only characterize virtual accessibility but may also enhance travel experience and physical accessibility (van Wee et al., 2013; Lu et al., 2014).

3.2 Relationship between VAG/PAG and Exogenous Variables, VALSC, and PALSC

In this section, we discuss the effects of exogenous variables, VALSC, and PALSC on the virtual accessibility engagement (VAG) outcomes and the physical accessibility engagement (PAG) outcomes. As a by-product, we also obtain the loadings of the PALSC construct on the four ordinal indicators of ease of commute without a car, ease of shopping without car, quality of bicycle lanes in the vicinity of the respondent's residence, and quality of roadway pavement in the vicinity of the respondent's residence. PALSC had the expected strong positive loading on each of these indicators (the table containing these coefficients is available in the online supplement at http://www.caee.utexas.edu/prof/bhat/ABSTRACTS/Accessibility/OnlineSupplement.pdf).

3.2.1 Virtual Accessibility Engagement (VAG) Outcome Variable Results

Table 3 provides the results for the VAG outcomes. The dependent outcome variables are arranged column-wise, and the exogenous variables are arranged row-wise. The estimates provide the effects of the exogenous variables on the latent propensities underlying the VAG outcomes. Other endogenous outcome variables are also allowed to impact the ordinal frequency of VAG outcomes (frequency of work from home, frequency of food delivery, and frequency of goods delivery) and the binary VAG outcome (whether main food shopping method is online or not) in a strictly recursive fashion, and any such statistically significant effects are presented at the bottom of the table. In Table 3, these effects correspond to the absence of vehicles owned by

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the respondent's household. However, this does not mean that PAG outcomes are first decided on and then VAG activities are determined in a sequential fashion. The modeling framework is a true joint model of both VAG and PAG outcomes because these outcomes are affected by the common underlying stochastic VALSC and PALSC constructs. Any endogenous effects in Table 3 (and Table 4 later) represent strictly recursive effects after accommodating the jointness in decision-making among all the VAG and PAG outcomes.

The constants in Table 3 (first row) associated with all four VAG outcomes, as well as the thresholds between the frequency categories for the three ordinal VAG outcomes (second row), do not have any substantive interpretations. In terms of variable effects on the frequency of working from home, women have a generally lower propensity to work from home than do men. In another relatively recent study, Singh et al. (2013) found that working women tend to be less likely to have the option of telecommuting, possibly because of the nature of their jobs and/or the lower autonomy and bargaining power they still seem to wield in the market place. The results also indicate that part-time workers have a lower propensity to work from home than full-time workers. This result has been observed by many telecommuting studies in the recent past (for example, see Asgari et al., 2014). It is possible that, since part-time employees already work for limited hours, employers are less willing to allow such employees to work frequently from home. Alternatively, it is also possible that part-time employees view their employment partly as a socializing break from home and consciously avoid working from home. Self-employed workers, on the other hand, have a higher propensity to work at home than salaried employees. Many studies have reported that the choice of self-employment corresponds to a preference for independence (see, for example, Benz and Frey, 2008; Dawson et al., 2014). Also, self-employed workers are free to choose their workplace, and can work from home without constraints placed by supervisors or company rules. Not surprisingly, a higher VASLC implies a higher propensity to work from home.

The effects of the variables on the main food shopping channel (online or otherwise) reveals that women are more likely than men to indicate that their household's main method of food shopping is online. While the respondents were selected so that she or he was the main food shopper for the household, women continue to be largely responsible for preparing food in the household (Food Standards Agency, 2016). Given these responsibilities, and the fact that all respondents are workers, women may be more time-constrained, and so may shop more online as

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the main food purchasing method for the household. Indeed, Jabs et al. (2007) reported that employed mothers experienced the greatest time scarcity. Further, the Office for National Statistics (UK) (ONS, 2016a) has also observed that women are more likely to buy food online. Income has the expected positive impact on the propensity that the main method for food shopping of a household is online (the net result is that the positive effect of income on online food shopping gets reinforced because income positively affects VALSC too, and VALSC also impacts the main food shopping channel, as discussed later). The positive income effect may be a combination of two considerations: (1) shopping for food online incurs delivery fees that increase the overall food expenditures, and higher income households are more easily able to absorb the higher costs, and (2) shopping for food online allows for a better selection of products as well as the purchase of refined and hard-to-find items, which are usually expensive and only consumed by wealthier individuals. Cao et al. (2012), for example, find that higher household incomes are associated with increased frequencies of online searching and purchase but not in-store shopping. Living in a metropolitan area (relative to living in non-metropolitan areas) negatively impacts the propensity that the main food shopping method will be online, consistent with the presence of a variety of grocery shopping places in close proximity in metro areas. Not surprisingly, a higher VALSC leads to a higher inclination for online food shopping. Finally, under the category of recursive endogenous effects, the absence of vehicles in the household positively impacts the main online food shopping channel, which is intuitive as it is more convenient to have food delivered directly to the home rather than carrying the items in non-motorized modes or transit (vehicle availability is introduced as a simple binary variable here because there was no statistically significant difference between the other three ordinal categories of "less than one per adult", "one per adult", and "more than one per adult"; thus, these three categories are combined into a base category with the "absence of motorized vehicles" as the base category).

The variable effects corresponding to the frequency of food delivery suggest that being a woman and having children in the household contributes to a higher frequency of food being delivered to the household (a child is defined as an individual 15 years of age or younger). These results reinforce earlier results, and probably reflect the constrained time budget for food preparation on a daily basis by working parents and women who usually are also responsible for child care and escorting activities (Buddelmeyer et al., 2017; Motte-Baumvol et al., 2017). Age

also has a significant effect on the frequency of food delivery. Older individuals (>40 years), relative to younger individuals, have a lower propensity to order food online or by phone and have the food delivered to their homes. This result may reflect habitual effects (habituated to traveling to the supermarket for groceries), or the fact that older individuals face more barriers while shopping online, as noted by Lian and Yen (2014). Consistent with earlier results, higher income households appear to have a higher frequency to have food delivered relative to lower income households. As expected, VALSC has a positive impact on the propensity determining the frequency of food delivery, reinforcing the direct age and income effects just discussed.

The final VAG outcome variable is the frequency of goods delivery. As expected, household income and VALSC positively impact the frequency of goods delivery, as does the absence of motorized vehicles in the household.

A final note about the VAG outcomes. All of these outcomes are impacted by VALSC, though none of them are influenced (at least statistically significantly speaking) by PALSC.

3.2.2 Physical Activity Engagement (PAG) Outcome Variable Results

Table 4 provides the results for the PAG outcomes (number and average durations of OH activity episodes in mandatory, maintenance, and discretionary activity purposes, motorized vehicle availability in the household, the average number of trips chained per tour, and average trip distance within a tour). The dependent variables are again arranged column-wise.

For the <u>count</u> outcomes (the number of activity episodes by purpose), the Table 4 coefficients represent the effects of the row exogenous variables on the thresholds in the generalized ordered-response recasting of the count models (see Castro et al., 2012), and the effects of endogenous variables (strictly recursive effects if present) and the latent constructs on the underlying latent propensity of the count variable. Also, the constant coefficients for these count outcome variables do not have any substantive interpretation. For the coefficients for the other exogenous variables, a positive coefficient shifts all the thresholds toward the right of the count propensity scale, which has the effect of reducing the probability of the zero count (see Castro et al., 2012). On the other hand, a negative coefficient shifts all the thresholds to the left of the count propensity scale, which has the effect of increasing the probability of the zero count. In short, a positive coefficient increases the non-zero count, while a negative coefficient increases the zero count. In addition to the effects mentioned above, for each count variable, we

tested a general count structure against a simpler Poisson structure. In our empirical analysis, the final model specifications for all the count outcomes collapsed to a Poisson generating process. For the ordinal variables (average duration of activities by purpose, motorized vehicle availability, and average number of trips per tour), the coefficients represent the impacts of the exogenous and endogenous variables on the continuous latent propensity, as in a usual ordered response framework. In the ordered response framework, there is a constant as well as K-1 thresholds, where K is the number of ordinal categories. To save on space, we do not present the thresholds for the ordinal variables in Table 4, but these are presented in the online supplement. For the continuous variable (average trip distance within a tour), the coefficient effects are straightforward.

Finally, vehicle availability is introduced as a determinant in other endogenous variables (as part of the endogenous effects) as a simple binary variable, for the same reason as in the case of the VAG outcomes. Similar reasons are behind the introduction of other ordinal endogenous variables (frequency of working from home, frequency of food deliveries, and frequency of goods delivery) as binary variables when including recursive endogenous effects.

Mandatory activity episodes: The results in Table 4 indicate that women with children are associated with fewer work episodes than women without children or men. This may be explained by the traditional societal role/expectation of mothers as the primary caregivers of children. It may also be a consequence of lower levels of work fragmentation, as discussed later. Employment related variables, such as employment status (part-time versus full-time) and employment type (employee versus self-employed), are good indicators of spatiotemporal characteristics associated with the work activity. As expected, part-time workers tend to have fewer work episodes than full-time workers. We do not observe a significant effect on average work activity episode duration, which may be a consequence of full-time workers leaving the office for lunch and breaking the work activity in two episodes that can be equivalent to a part-time shift. We interacted gender with employment status and observe that full-time working women have longer average duration of mandatory activity episodes compared to part-time working women and full- or part-time working men. Together with the previous result, the implication is that full-time working women have less flexibility to fragment temporally their work activities compared to full-time working men. This diminished ability to fragment work

may be associated with the nature of the jobs that women predominantly hold (ONS, 2013, ONS, 2016b, and ILO, 2016), or the elimination of the lunch break in exchange for leaving earlier to meet other household responsibilities (Johnson et al., 2013; Fan, 2017). There is no statistically significant difference between self-employed individuals and employees in the number of work episodes, but self-employed individuals have a lower average duration of each work episode. As mentioned earlier, self-employed individuals are responsible for their own business and have higher levels of work flexibility. Virtual accessibility (VALSC) reduces both the number and the duration of work episodes. The physical accessibility latent stochastic construct (PALSC) does not have statistically significant effects on the number or duration of work activity episodes; individuals are usually willing to overcome physical accessibility barriers to travel to work. Finally, in addition to the VALSC effect, working for home one or more times per week also has a direct effect of reducing the average duration of mandatory activities episodes, pointing to the direct substitution of time allocated for OH work and work at home.

Maintenance activity episodes: Older individuals (fifty years of age and older) tend to have more non-zero shopping activity episodes (which is reinforced by the indirect effect of age through the VALSC variable), a finding supported by Zhou and Wang (2014). As observed earlier, the fifty-plus age segment is the age group with the lowest virtual accessibility and does not tend to shop online frequently, which may encourage in-store shopping. Additionally, older individuals tend to have more free time than their younger counterparts. Age, however, does not have a direct significant impact on average maintenance episode duration. Part-time working women are associated with more maintenance episodes, while women in general have longer maintenance episodes, again reinforcing the notion that women are usually responsible for a greater share of household-related maintenance activities. Living in a metropolitan area is associated with an increase in physical maintenance activity duration, in keeping with the negative effect of this variable earlier on the "main food shopping method being online".

VALSC negatively impacts the number of maintenance activities but does not seem to affect duration of OH maintenance activities. Curiously, the PALSC construct negatively impacts the number, and positively impacts the duration, of maintenance activities, suggesting that perceptions of high physical accessibility do not lead to the fragmentation of maintenance activities. To the contrary, individuals who perceive ease of access to opportunities tend to

concentrate their maintenance activities in fewer and longer episodes. While not immediately intuitive, this does support the possible notion that a higher PALSC raises the attractiveness of leisure/discretionary activity pursuits in person, thereby making people travel less often to pursue maintenance activities. Also, notwithstanding the fact that our PALSC construct could be enhanced by having better BE attributes in the PAM set, the takeaway is that there is a need to consider both PALSC as well as VALSC jointly, as well as consider the comprehensive set of VAG and PAG participations in multiple activity purposes simultaneously, as our analysis undertakes Overall, notwithstanding the fact that our PALSC construct is mostly measuring access to activities without the use of an automobile and could be enhanced by having better BE attributes in the PAM set, the takeaway is that there is a need to consider both PALSC and VALSC jointly, as well as jointly consider the comprehensive set of VAG and PAG participations in multiple activity purposes (as our analysis undertakes).

The effects of the endogenous outcome variables suggests that individuals who work from home one or more times pursue shorter maintenance episodes. As expected, individuals who have food delivered to their homes at least once a week tend to pursue shorter OH maintenance activities. Individuals who work long hours have fewer and shorter maintenance activity episodes, possibly a consequence of time scarcity. Finally, individuals living in households without motorized vehicles also tend to pursue fewer maintenance activities.

Discretionary activity episodes: Overall, the presence of children in the household is associated with fewer out-of-home discretionary activity episodes for both men and women, with men being more negatively affected. On the other hand, women, in general, seem to pursue shorter discretionary episodes. Individuals who live in metropolitan areas appear to undertake longer discretionary activity episodes, which is likely a consequence of the type of discretionary activities undertaken in metropolitan areas.

A higher virtual accessibility (VALSC) is associated with an increased number of out-of-home leisure and social activity episodes. People with high virtual accessibility have expanded access to knowledge about recreational events. Kenyon (2010) found that interaction with the internet increases the in-person physical social interaction. The impacts of PALSC, total work duration, and the absence of motorized vehicles on the number and durations of OH discretionary activity episodes are similar to the impacts on maintenance episodes.

Motorized vehicle availability, trip chaining, and average trip distance results: Multi-worker households are likely to own more motorized vehicles per adult than single-worker households, consistent with the typically higher need of vehicles in households with multiple workers. The effect of residing in a metropolitan area (as opposed to in non-metro areas) is precisely the opposite, again consistent with the better transit facilities in metropolitan areas and the lower need for personal vehicles there. In our analysis, the virtual accessibility VALSC measure has a positive effect on vehicle ownership. However, it is possible that newer data sets with travel behavior data that already incorporate the use of carsharing and ride-hailing services would provide evidence that virtual accessibility decreases vehicle ownership. For example, Lavieri et al. (2017a, 2017b) found that tech-savvy individuals are less likely to own vehicles. Higher levels of PALSC measures (based on accessibility by non-auto modes), as expected, leads to lower motorized vehicle ownership and, therefore, availability.

Trip chaining behavior, in our analysis, is based on examining the average number of trips per home-based tour. Presence of children in the household contributes to higher chaining behavior, which is expected considering that parents accommodate escorting activities within their work, maintenance and discretionary routine. Part-time working women chain trips more than full-time workers (men and women) and male part-time workers. As discussed earlier, women are usually responsible for most household shopping activities and child escorting, especially when employed part-time; therefore, it is not surprising that they perform more complex tours to fit all their responsibilities in their schedules (see Primerano et al., 2008 for a similar result). Virtual accessibility increases trip chaining propensity, an indication that ICT use may contribute to better planning of activity locations and efficient scheduling. The physical accessibility PALSC measure, on the other hand, has a strong negative effect on trip chaining, perhaps because of the ease of reaching activities independently from the household. Having goods delivered to the home at least once a week has a negative impact on trip chaining, suggesting a possible reduction in maintenance activity episodes that are usually chained with other participations within multi-purpose tours.

Finally, lower average trip distances within a tour are observed for individuals living in households with children. Children usually attend schools and have other activities located close to the residence, which may explain the above result. VALSC increases the average distance

traveled per trip, suggesting that virtual access encourages individuals to expand their activity space, as also observed by Miranda-Moreno et al. (2012). As expected, PALSC reduces trip distances.

3.3. Summary of Results and Implications

The results above indicate the intricate and interwoven effects of virtual and physical accessibility (as characterized by VALSC and PALSC, which are themselves impacted by VAMs and PAMs) on both virtual and physical activity engagements (VAG and PAG) for multiple activity purposes. Particularly important to note is that each of the stochastic VALSC and PALSC impact multiple VAG and PAG measures simultaneously, immediately underscoring the notion that studies that consider VAG as exogenous variables in analyzing PAG measures are fraught with a fundamental endogeneity problem. In particular, based on our results, after controlling for observed factors, unobserved factors that increase the propensity to engage in VAG (the VAG includes frequency of work from home, and shopping for goods online) through the VALSC latent construct also impact most PAG outcomes (also, VALSC and PALSC exhibit a moderate positive correlation). For example, individuals with a higher degree of self-efficacy or intensity of exploration orientation will tend to have a higher VALSC and PALSC (the latter due to the positive correlation between VALSC and PALSC), which then would make these individuals simultaneously more pre-disposed to working from home, using an online platform to purchase goods, and participating less in mandatory and maintenance OH activities. Not taking into account these unobserved VALSC and PALSC effects can result in the incorrect conclusion that telecommuting and frequency of goods delivered, by themselves, lead to a substitution effect on maintenance activity participation.

To further demonstrate the misleading effects that can result from ignoring the package nature of VAG and PAG outcomes, we compute average treatment effects (ATE) (see Heckman and Vytlacil, 2000, 2001) of the impacts of the VAG outcomes on the PAG outcomes, as implied by our GHDM model and the simpler independent heterogeneous data model (IHDM) model. The IHDM model excludes the VALSC and PALSC constructs, but includes the exogenous determinants of these latent constructs as explanatory variables as well as considers all statistically significant VAG outcome effects on PAG outcomes (that is, incorrectly considers the VAG outcomes as exogenous, as has been commonly done in the extant literature). This is an

independent model because of the absence of the unobserved correlation across the VAG and PAG outcomes and also across outcomes within each of the VAG and PAG outcome subsets (engendered through the stochastic VALSC and PALSC in our GHDM model). The ATE of each VAG outcome on the PAG outcomes provides the expected PAG outcome change for a random individual if the individual's VAG outcome changed from one state to another.[3]

The analyst can compute the ATE for all combinations of state changes within each VAG outcome. To streamline the presentation, we focus on the ATE for the following state changes for two VAG outcomes: (a) from "twice a year or less" (for ease, we will refer to this state as one of non-telecommuting) to "one or more times a week" for the frequency of working from home, and (b) from "twice a year or less" to "one or more times a week" for the frequency of goods delivery (these two VAG outcomes were chosen because, for the current data set, they were the only ones to present direct effects on PAG in the GHDM and/or IHDM specification). Further, because the two VAG outcomes both do not have any statistically significant recursive impacts on the motorized vehicle availability and average trip distance PAG outcomes, we do not consider the ATE effects for these two PAG outcomes. Additionally, to keep the ATE results simple and interpretable, we assign a cardinal value for each of the ordinal categories (representing the mid-point of the ordinal threshold values) for the average durations and average number of trips per tour PAG outcomes. For example, an individual whose average maintenance episode duration falls in the 1-2 hours ordinal category is assigned a cardinal value of average maintenance episode duration of 1.5 hours. The ATE for such variables then provides the change in the expected durations or number of trips per tour due to a change in state of the VAG outcome. The procedure to compute these ATE effects is the same as that in Astroza et al. (2017).

The estimated ATE values (and standard errors) are provided in Table 5 for both the GHDM and IHDM models. The "treatment" variables (that is, the VAG outcomes in our case) are arranged column-wise, while the PAG outcome variables are arranged row-wise. The first entry under the first numeric column with the "IHDM model" heading indicates that a random individual who switches states from being a non-telecommuter to becoming a telecommuter

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[3] The ATE measures can be computed to reflect the effect of each VAG outcome on the multivariate combination of all the PAG outcomes at once. Further, it is possible to compute also the ATE effect for a multivariate state change of the VAG outcomes at once. But the number of multivariate combinations explode quickly. For a more intuitive presentation, we focus on ATE effects that represent univariate marginal effects of state changes in each VAG outcome variable on each univariate marginal PAG outcome.

(working from home one or more times a week) is, on average, likely to reduce the number of mandatory activity episodes during the week by 0.650 episodes (standard error of 0.322). Equivalently, if 100 random individuals changed their states from non-telecommuting to telecommuting, the point estimate indicates that the number of mandatory activity episodes per week across those 100 individuals would reduce by about 65 episodes. Other point estimates may be similarly interpreted. The results from Table 5 are revealing in that the simpler IHDM model (that ignores the package decision nature) consistently <u>overestimates direct substitution effects</u> between the VAG and PAG outcomes because it ignores the presence of common observed and unobserved factors affecting the VAG and PAG outcomes in the form of the VALSC and PALSC latent constructs. Thus, in the context of the number of mandatory activity episodes, our results indicate that individuals who are very tech-savvy with a high VALSC would gravitate toward jobs that allow them to telecommute and reduce the need to travel into work, rather than the very act of telecommuting itself being the cause of decreasing the number of mandatory episodes (observe the positive effect of VALSC on the "frequency of working from home" in Table 3 and the negative effect of VALSC on "number of mandatory activity episodes in Table 4). Similarly, while our GHDM shows a neutrality effect between goods delivery frequency and the number of maintenance episodes, the IHDM shows a substitution of almost half of an episode per individual per week for maintenance episodes (again because VALSC positively affects "frequency of goods delivery" and negatively affects "number of maintenance activity episodes"). Similar overestimations may be noticed from the IHDM model regarding the impacts of the VAG outcomes on the number of discretionary activity episodes (for the frequency of goods delivery), and the average durations of mandatory and maintenance activity episodes (for the frequency of working from home). The impact of goods delivery on trip chaining behavior, on the other hand, is underestimated by the IHDM (see the last row of Table 5). As we observe in Tables 3 and 4, our GHDM model suggests that tech-savvy individuals intrinsically have goods delivered more frequently to their homes and also may use ICT for effective chaining of activities (based on the positive VALSC effect on both the frequency of goods delivery and average number of trips per tour). Because the IHDM model ignores this positive association, it underestimates the direct negative impact of foods delivery on trip chaining tendency.

The overall implication of the results above is that if VAG and PAG outcomes are not modeled jointly as a package, and VAG outcomes are considered exogenous to PAG outcomes (as has been the norm in existing studies), it can lead to misleading results regarding the "six effects" influence on PAG outcomes.

3.4. Model Fit

As we discuss in this section, the GHDM model also provides a better data fit than the IHDM model, validating our joint methodology for analyzing VAG and PAG outcomes rather than assuming VAG outcomes as exogenous to PAG outcomes. The GHDM and the IHDM models are not nested, but they may be compared using the composite likelihood information criterion (CLIC) (see Bhat et al., 2016 for details). The model that provides a higher value of CLIC is preferred. Another way to examine the performance of the two models is to compute the equivalent GHDM predictive household-level likelihood value and computing the log-likelihood value across all respondents at convergence. The corresponding IHDM predictive log-likelihood value may also be computed. Then, one can compute the adjusted likelihood ratio index of each model with respect to the log-likelihood with only the constants. To test the performance of the two models statistically, the non-nested adjusted likelihood ratio test may be used (see Ben-Akiva and Lerman, 1985, page 172). This test determines if the adjusted likelihood ratio (ALR) indices of two non-nested models are significantly different. In particular, the test determines the probability that the difference in the ALR indices could have occurred by chance in the asymptotic limit. A small value of the probability of chance occurrence indicates that the difference is statistically significant and that the model with the higher value of adjusted likelihood ratio index is to be preferred.

We also evaluate the data fit of the two models intuitively and informally at both the disaggregate and aggregate levels. To do so, we restrict ourselves to two VAG outcomes (frequency of working from home and frequency of food delivery), and two PAG outcomes (number of maintenance activity episodes and discretionary activity episodes). Even with this restricted set of dimensions, there are too many combinations, and so we focus on working from home two times a year or less and two possible alternatives within each of the remaining three outcomes (leading to a total of 8 joint combinations). These two possible alternatives correspond to the two most frequently chosen ordinal/count categories within each of the remaining three

outcomes. We then compute multivariate predictions for these eight combinations. At the disaggregate level, for the GHDM model, we estimate the probability of the observed multivariate outcome for each individual and compute an average (across individuals) probability of correct prediction at this four-variate level. Similar disaggregate measures are computed for the IHDM model. At the aggregate level, we design a heuristic diagnostic check of model fit by computing the predicted aggregate share of individuals in each of the eight combination categories. The predicted shares from the GHDM and the IHDM models are compared to the actual shares, and the absolute percentage error (APE) statistic is computed.

The composite marginal likelihoods of the GHDM and IHDM models came out to be −1,058,575 and −1,066,129, respectively. Other measures of fit are provided in Table 6a. The GHDM shows a better goodness-of-fit on the basis of the CLIC statistic, the predictive log-likelihood values and the predictive adjusted likelihood ratio indices. The same result is obtained from the non-nested likelihood ratio statistic; the probability that the adjusted likelihood ratio index difference between the GHDM and the IHDM models could have occurred by chance is literally zero. The average probability of correct prediction is 0.014 for the GHDM model, and 0.011 for the IHDM model. At the aggregate level, the eight selected combinations at the four-variate level are identified in Table 6b. For each of these combinations, the shares predicted by the GHDM model are either superior to the IHDM model or about the same as the IHDM model. Across all eight combinations, the average APE is 23.285 for the GHDM model compared to 31.015 for the IHDM. The aggregate fit measures in Table 6b reinforce the disaggregate level results in Table 6a. In summary, the results show that the GHDM model proposed here outperforms the IHDM model in data fit, validating the view that the PAG and VAG outcomes need to be modeled jointly as a package.

5. CONCLUSIONS

This paper has proposed a modeling framework to study the effects of information and communication technologies (ICT) on activity and travel behavior based on physical and virtual accessibility. We utilized the generalized heterogeneous data model (GHDM) approach that allows for the joint modeling of multiple outcomes of mixed types, including count, continuous, and ordinal variables. The data used was extracted from the 2011 and 2012 National Travel Survey in Great Britain, which collected information on individual sociodemographic

characteristics, attitudes, stated frequency of remote purchases and work, as well as seven-day trip diaries.

Our study provides several insightful results and observations. First, we identified that young wealthy individuals have the highest levels of virtual accessibility. Also, individuals aged fifty or over have lower levels of virtual accessibility compared to younger individuals. At the same time, while age does not reveal a significant effect on physical accessibility in our study, potential social exclusion due to diminished physical accessibility for elders is a relevant concern as developed countries face aging populations (see, for example, Walsh et al., 2016 and King, 2016). Since this older segment does not seem likely to benefit substantially from virtual accessibility as an overall accessibility enhancer, actions to increase their physical accessibility directly or to educate them on how to take advantage of virtual accessibility seem urgent.

Second, by focusing on a sample of individuals who are workers at the same time that they are the main food shoppers of their households, and by including interactions between gender, employment status, and presence of children, we were able to analyze gendered social roles and the potential benefits that virtual accessibility can bring to different individuals. Our results point to the busy and time-squeezed schedules of working mothers who seem to undertake major household and childcare responsibilities (the "second shift", as referred to by sociologist Hochschild, 1997), and who could benefit from increased virtual and physical accessibility through welfare policies that enhance spatio-temporal flexibility and encourage social-inclusion.

Third, our construction of the latent accessibility variables VALSC and PALSC, and their effects on multiple VAG and PAG outcome variables, indicate that choices regarding participation and duration in virtual and physical pursuits of multiple activity purposes are jointly determined as a package. Considering a singular activity purpose for analysis (such as only shopping) or considering virtual pursuits to be exogenous in understanding ICT effects on physical pursuits can provide misinformed results. In particular, our study finds that the main effect between virtual activity engagements (VAG) and physical activity engagements (PAG) is one of neutrality (after accommodating the package nature of these choices). Thus, for example, our results indicate that a policy promoting a higher level of virtual shopping (goods deliveries to the home) will not necessarily reduce the number of in-person visits to the stores. While the final results may vary based on context, data, and the segment of the population studied, our study has

provided a conceptual and analytic structure to be able to consider the jointness of PAG and VAG outcomes, which we hope will lead to richer empirical studies in the future and more informed policy actions. Further, our structure is also able to consider episode planning dimensions (through such instruments as vehicle availability and episode chaining/trip planning) as co-endogenous package variables.

Fourth, our analysis includes multiple activity purposes at the same time, both virtually and physically (though we acknowledge that our analysis would have been substantially enhanced if the data had had some measures related to online socializing and recreation, in addition to online maintenance activity participation). By considering multiple activity purposes, our analysis is able to provide the rich interactions and interplay in activity engagement across both the virtual and real worlds. It also recognizes that the determinants of virtual activity engagement vary based on activity purpose, just as in the case of physical activity engagement. It also enables us to see the "big picture" regarding overall activity accessibility afforded to specific segments of society. For example, our analysis indicates that women, relative to men, have a generally lower propensity (ability/opportunity) to work from home, have less flexibility to fragment temporally their work activities (especially when working full-time), pursue maintenance activities for longer durations per episode and have more episode chaining as part of their daily and weekly activity patterns (when working part-time). Further, parents (fathers and mothers), in general, perceive lower physical accessibility levels and tend to pursue fewer discretionary activity episodes. The clear implication is that women and parents of small children suffer from both low physical accessibility as well as less flexibility to telecommute, appear to be time-poor, and tend to be socially excluded. These results suggest that, even if women have access to the internet, they may not be able to harness that access to increase their overall activity engagement experience. Perhaps there is a need to rigorously evaluate and continue to consider the implementation of work-friendly policies for women and parents in general. Policies that promote physical activity and or provide recreational opportunities at the work place may also be beneficial in addressing time poverty and social exclusion considerations.

Finally, as an observation, and as with all research studies, there are limitations of the current study that suggest future directions. Most of these limitations are related to data availability. In particular, improved data on virtual accessibility measures or VAMs (data on smartphone ownership, perceptions related to virtual accessibility, and use of real time-

information), physical accessibility measures or PAMs (geocoded data of activity locations and residences, which can be used to develop improved BE attributes), and VAG outcomes (diaries of virtual activities, including multi-tasking) are needed to harness the full potential of our proposed framework and to provide a more complete analysis of joint activity participation in both the virtual and physical worlds.

REFERENCES

Asgari, H., Jin, X. and Mohseni, A., 2014. Choice, frequency, and engagement: Framework for telecommuting behavior analysis and modeling. *Transportation Research Record: Journal of the Transportation Research Board*, 2413, 101-109.

Astroza, S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Lavieri, P.S. and Dias, F.F., 2017. Analysis of the impact of technology use on multimodality and activity travel characteristics. *Transportation Research Record: Journal of the Transportation Research Board*, 2666, 19-28.

Bandura, A., 1982. Self-efficacy mechanism in human agency. *American Psychologist*, 37(2), 122-147.

Ben-Akiva, M., Lerman, S.R., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*, The MIT Press, Cambridge, Massachusetts.

Berliner, R.M., Malokin, A., Circella, G. and Mokhtarian, P.L., 2015. Travel-based multitasking: Modeling the propensity to conduct activities while commuting. Paper no. 15-5018. Presented at the 94th Annual Meeting of the Transportation Research Board, Washington DC, January.

Benz, M. and Frey, B.S., 2008. Being independent is a great thing: Subjective evaluations of self-employment and hierarchy. *Economica*, 75(298), 362-383.

Bhat, C.R., 2015. A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B*, 79, 50-77.

Bhat, C.R., Astroza, S., Bhat, A.C. and Nagel, K., 2016. Incorporating a multiple discrete-continuous outcome in the generalized heterogeneous data model: Application to residential self-selection effects analysis in an activity time-use behavior model. *Transportation Research Part B*, 91, 52-76.

Buddelmeyer, H., Hamermesh, D.S. and Wooden, M., 2017. THE stress cost of children on moms and dads. *European Economic Review*, in press.

Cao, X.J., Xu, Z. and Douma, F., 2012. The interactions between e-shopping and traditional in-store shopping: An application of structural equations model. *Transportation*, 39(5), 957-974.

Castro, M., Paleti, R. and Bhat, C.R., 2012. A latent variable representation of count data models to accommodate spatial and temporal dependence: Application to predicting crash frequency at intersections. *Transportation Research Part B*, 46(1), 253-272.

Couclelis, H., 2000. From sustainable transportation to sustainable accessibility: Can we avoid a new tragedy of the commons? In *Information, Place, and Cyberspace*, 341-356, Springer Berlin Heidelberg.

Curl, A., Nelson, J.D. and Anable, J., 2011. Does accessibility planning address what matters? A review of current practice and practitioner perspectives. *Research in Transportation Business & Management*, 2, 3-11.

Dawson, C., Henley, A. and Latreille, P., 2014. Individual motives for choosing self-employment in the UK: Does region matter? *Regional Studies*, 48(5), 804-822.

Ding, Y. and Lu, H., 2017. The interactions between online shopping and personal activity travel behavior: An analysis with a GPS-based activity travel diary. *Transportation*, 44(2), 311-324.

Fan, Y., 2017. Household structure and gender differences in travel time: Spouse/partner presence, parenthood, and breadwinner status. *Transportation*, 44(2), 271-291.

Food Standards Agency, 2016. How often do you cook or prepare food for yourself and others? Accessed on 06/22/2017. https://www.statista.com/statistics/429292/frequency-of-cooking-meals-for-yourself-in-the-united-kingdom-uk/

Geurs, K.T. and van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography*, 12(2), 127-140.

Heckman, J.J. and Vytlacil, E.J., 2000. The relationship between treatment parameters within a latent variable framework. *Economics Letters*, 66(1), 33-39.

Heckman, J.J. and Vytlacil, E., 2001. Policy-relevant treatment effects. *American Economic Review*, 91(2), 107-111.

Helsper, E.J. and Eynon, R., 2010. Digital natives: Where is the evidence? *British Educational Research Journal*, 36(3), 503-520.

Hochschild, A.R. (1997). *The Time Bind: When Work Becomes Home and Home Becomes Work*, Holt, New York, NY.

Hu, L. and He, S.Y., 2016. Association between telecommuting and household travel in the Chicago metropolitan area. *Journal of Urban Planning and Development*, 142(3), p.04016005.

Hubers, C., Dijst, M. and Schwanen, T., 2015. The fragmented worker? ICT, coping strategies and gender differences in the temporal and spatial fragmentation of paid labour. *Time & Society*, 27(1), 92-130.

International Labour Organisation (ILO), 2016. *Women at work: Trends 2016*. ILO, Geneva, Switzerland.

Jabs, J., Devine, C.M., Bisogni, C.A., Farrell, T.J., Jastran, M. and Wethington, E., 2007. Trying to find the quickest way: Employed mothers' constructions of time for food. *Journal of Nutrition Education and Behavior*, 39(1), 18-25.

Johnson, S., Li, J., Kendall, G., Strazdins, L. and Jacoby, P., 2013. Mothers' and fathers' work hours, child gender, and behavior in middle childhood. *Journal of Marriage and Family*, 75(1), 56-74.

Kenyon, S., 2010. The impacts of Internet use upon activity participation and travel: Results from a longitudinal diary-based panel study. *Transportation Research Part C*, 18(1), 21-35.

Kenyon, S. and Lyons, G., 2007. Introducing multitasking to the study of travel and ICT: Examining its extent and assessing its potential importance. *Transportation Research Part A*, 41(2), 161-175.

Kenyon, S., Rafferty, J. and Lyons, G., 2003. Social exclusion and transport in the UK: A role for virtual accessibility in the alleviation of mobility-related social exclusion?. *Journal of Social Policy*, 32(3), 317-338.

King, M.J., 2016. Safety while walking among older people: The intersection of mobility, road safety, physical fragility, gender and fears about personal safety. *International Journal of Psychology*, 51, 1144.

Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S. and Dias, F.F., 2017a. Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. *Transportation Research Record: Journal of the Transportation Research Board*, 2665, 1-10.

Lavieri, P.S., Garikapati, V.M., Bhat, C.R. and Pendyala, R.M., 2017b. Investigation of heterogeneity in vehicle ownership and usage for the millennial generation. *Transportation Research Record: Journal of the Transportation Research Board*, 2664, 91-99.

Lee, R.J., Sener, I.N., Mokhtarian, P.L. and Handy, S.L., 2017. Relationships between the online and in-store shopping frequency of Davis, California residents. *Transportation Research Part A*, 100, 40-52.

Lian, J.W. and Yen, D.C., 2014. Online shopping drivers and barriers for older adults: Age and gender differences. *Computers in Human Behavior*, 37, 133-143.

Lila, P.C. and Anjaneyulu, M.V.L.R., 2016. Modeling the impact of ICT on the activity and travel behaviour of urban dwellers in Indian context. *Transportation Research Procedia*, 17, 418-427.

Liu, N. and Yu, R., 2017. Identifying design feature factors critical to acceptance and usage behavior of smartphones. *Computers in Human Behavior*, 70, 131-142.

Lu, R., Chorus, C.G. and Van Wee, B., 2014. The effects of different forms of ICT on accessibility–a behavioural model and numerical examples. *Transportmetrica A: Transport Science*, 10(3), 233-254.

Matous, P., 2017. Complementarity and substitution between physical and virtual travel for instrumental information sharing in remote rural regions: A social network approach. *Transportation Research Part A*, 99, 61-79.

Miranda-Moreno, L.F., Eluru, N., Lee-Gosselin, M. and Kreider, T., 2012. Impact of ICT access on personal activity space and greenhouse gas production: Evidence from Quebec City, Canada. *Transportation*, 39(5), 895-918.

Motte-Baumvol, B., Bonin, O. and Belton-Chevallier, L., 2017. Who escort children: Mum or dad? Exploring gender differences in escorting mobility among Parisian dual-earner couples. *Transportation*, 44(1), 139-157.

ONS, 2013. Women in the labour market: 2013. Accessed on 07.07.2017. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemplo yeetypes/articles/womeninthelabourmarket/2013-09-25

ONS, 2016a. Share of individuals who made purchases online in Great Britain in 2008-2016, by gender. Accessed on 06.22.2017. https://www.statista.com/statistics/276076/online-purchasing-penetration-in-great-britain-by-gender/

ONS, 2016b. EMP04: Employment by occupation. Accessed on 07.07.2017. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemplo yeetypes/datasets/employmentbyoccupationemp04

Páez, A., Scott, D.M. and Morency, C., 2012. Measuring accessibility: Positive and normative implementations of various accessibility indicators. *Journal of Transport Geography*, 25, 141-153.

Pawlak, J., Polak, J.W. and Sivakumar, A., 2015. Towards a microeconomic framework for modelling the joint choice of activity–travel behaviour and ICT use. *Transportation Research Part A*, 76, 92-112.

Primerano, F., Taylor, M.A., Pitaksringkarn, L. and Tisato, P., 2008. Defining and understanding trip chaining behaviour. *Transportation*, 35(1), 55-72.

Ren, F. and Kwan, M.P., 2009. The impact of the Internet on human activity-travel patterns: Analysis of gender differences using multi-group structural equation models. *Journal of Transport Geography*, 17(6), 440-450.

Salomon, I., 1986. Telecommunications and travel relations: a review. *Transportation Research Part A*, 20(3), 223-238

Singh, P., Paleti, R., Jenkins, S. and Bhat, C.R., 2013. On modeling telecommuting behavior: Option, choice, and frequency. *Transportation*, 40(2), 373-396.

Taylor, E., Humphrey, A., Pickering, K. and Tipping, S., 2013. National Travel Survey 2012 Technical Report. Department for Transport, London.

Tranos, E., Reggiani, A. and Nijkamp, P., 2013. Accessibility of cities in the digital economy. *Cities*, 30, 59-67.

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.

van Wee, B., Geurs, K. and Chorus, C., 2013. Information, communication, travel behavior and accessibility. *The Journal of Transport and Land Use*, 6(3), 1-16.

Walsh, K., Scharf, T. and Keating, N., 2016. Social exclusion of older persons: A scoping review and conceptual framework. *European Journal of Ageing*, 14(1), 81-98.

Wang, D. and Law, F.Y.T., 2007. Impacts of Information and Communication Technologies (ICT) on time use and travel behavior: A structural equations analysis. *Transportation*, 34(4), 513-527.

Yu, H. and Shaw, S.L., 2008. Exploring potential human activities in physical and virtual spaces: A spatio-temporal GIS approach. *International Journal of Geographical Information Science*, 22(4), 409-430.

Zhou, Y. and Wang, X.C., 2014. Explore the relationship between online shopping and shopping trips: An analysis with the 2009 NHTS data. *Transportation Research Part A*, 70, 1-9.

Zhu, P., 2012. Are telecommuting and personal travel complements or substitutes? *The Annals of Regional Science*, 48(2), 619-639.
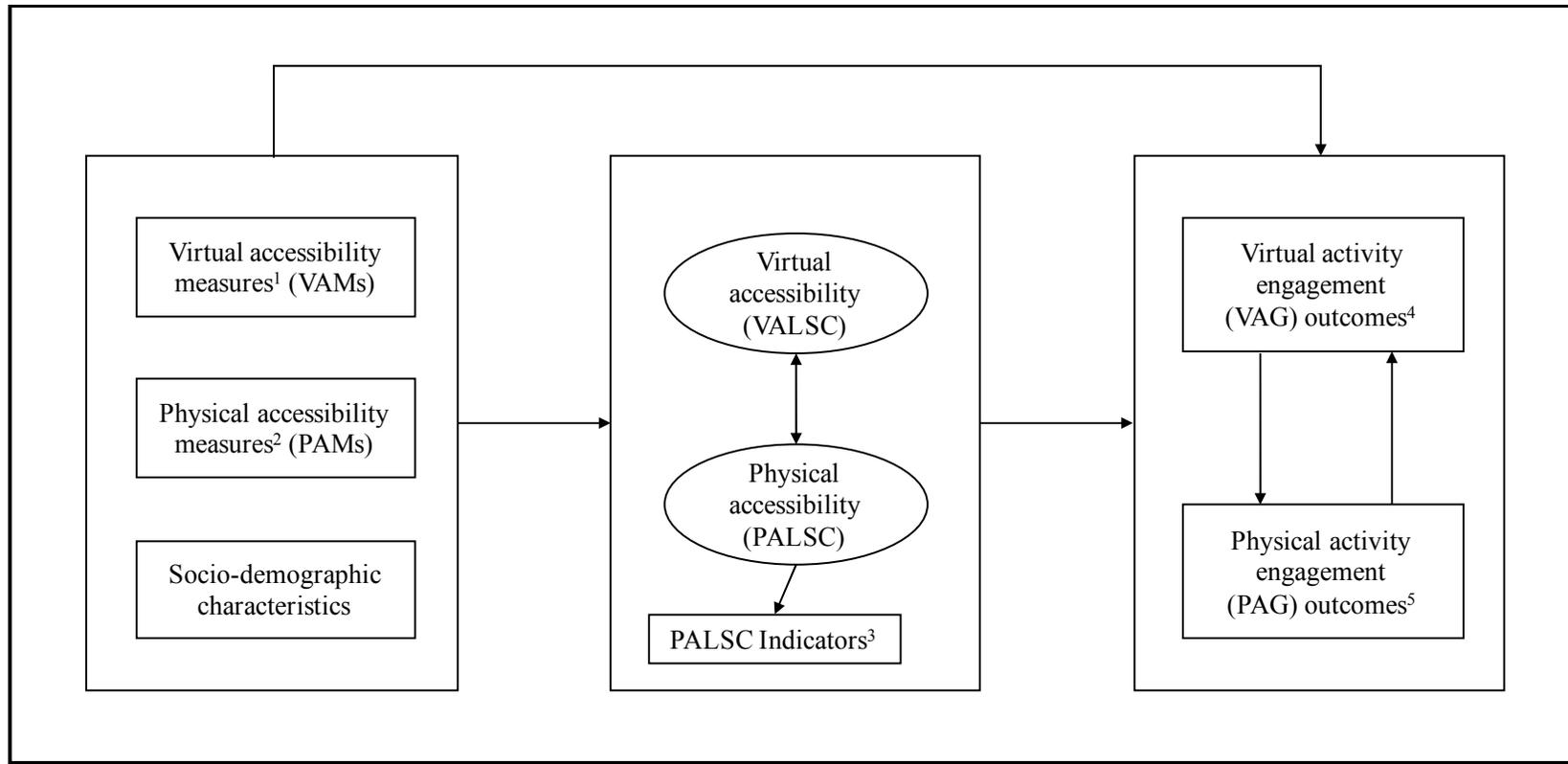
FIGURE 1 Conceptual and Analytic Framework

[1]The Virtual accessibility measures include occupation type, and internet availability.

[2]The Physical accessibility measures include travel time to the nearest hospital, travel time to the nearest shopping center, and travel time to the nearest rail station.

[3]The PALSC indicators include ease of commute without a car, ease of shopping without car, quality of bicycle lanes in the vicinity of the respondent's residence, and quality of roadway pavement in the vicinity of the respondent's residence.

[4]The VAG outcomes include frequency of work from home, whether main food shopping method is online or not, frequency of food delivery, and frequency of goods delivery.

[5]The PAG outcomes include the number and average duration of mandatory activity episodes, maintenance activity episodes, and discretionary activity episodes, vehicle availability in the household, the average number of trips per tour, and average trip distance per tour.

TABLE 1 Virtual Activity Engagement (VAG) and Physical Activity Engagement (PAG) Outcome Variables

VAG outcome variables					
Variable	Count	%	Variable	Count	%
Freq. of working at home			**Frequency of food delivery**		
Twice a year or less	2,704	81.5	Twice a year or less	2,207	66.5
Less than once per month	215	6.5	Less than once per month	486	14.6
Less than once per week	157	4.7	Less than once per week	335	10.1
One or more times per week	243	7.3	One or more times per week	291	8.8
			Frequency of goods delivery		
Main food purchase method is online			Twice a year or less	323	9.7
No	3,090	93.1	Less than once per month	632	19.0
Yes	229	6.9	Less than once per week	1445	43.5
			One or more times per week	919	27.8

PAG outcome variables				
Variables	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Number of mandatory episodes per week	0	39	3.9	3.2
Number of maintenance episodes per week	0	14	2.1	1.8
Number of discretionary episodes per week	0	35	3.0	3.2
Average trip distance (km)	0.3	138.5	9.3	10.0

Variable	Count	%	Variable	Count	%
Average duration of mandatory episode			**Average duration of discretionary episode**		
No episode in the survey week	606	18.3	No episode in the survey week	846	25.5
Less than 2 hours	188	5.7	Less than 1 hour	471	14.2
2-4 hours	399	12.0	1-2 hours	916	27.6
4-6 hours	547	16.5	2-3 hours	587	17.7
6-8 hours	678	20.4	More than 3 hours	499	15.0
8 or more	901	27.1	**Average number of trips per tour**		
Average duration of maintenance episode			2 trips	1061	32.0
No episode in the survey week	678	20.4	2-2.5 trips	1274	38.4
Less than 0.5 hour	615	18.5	2.5-3 trips	581	17.5
0.5-1 hour	846	25.5	More than 3 trips	403	12.1
1-2 hours	780	23.5	**Motorized vehicle availability**		
More than 2 hours	400	12.1	Absence of a vehicle	444	13.4
			Less than 1 per adult	982	29.6
			1 per adult	1678	50.5
			More than 1 per adult	215	6.5

TABLE 2 Structural Equations Model Results

Virtual Accessibility Latent Stochastic Construct (VALSC)		
Socio-demographic variables	**Coefficient**	**t-stat**
Age (base: 17 to 49 years old)		
50 or more years old	-0.163	-3.29
Education (base: less than degree-level)		
Degree-level or above	0.150	2.95
Household income (base: less than £50,000)		
£50,000 and over	0.124	1.95
Virtual accessibility measures (VAMs)	**Coefficient**	**t-stat**
Occupation type (base: routine, manual, intermediate occupations)		
Managerial and professional jobs	0.234	4.22
Internet availability (base: has Internet connection at home)		
Does not have Internet connection at home	-0.127	-1.95
Physical Accessibility Latent Stochastic Construct (PALSC)		
Socio-demographic variables	**Coefficient**	**t-stat**
House type (base: detached or semi-detached)		
Townhome	0.301	5.90
Apartment/flat	0.783	9.29
Household tenure status (base: owner/buying or other)		
Renter	0.585	9.79
Residential location (base: non-metropolitan area)		
Metropolitan area	0.336	5.78
Physical accessibility measures (PAMs)	**Coefficient**	**t-stat**
Travel time to the nearest hospital (hours)	-0.455	-5.64
Travel time to the nearest shopping center (hours)	-0.537	-4.95
Travel time to the nearest rail station (hours)	-0.432	-5.72
Correlation between VALSC and PALSC	**0.267**	**6.11**

TABLE 3 Virtual Accessibility Engagement (VAG) Outcome Variable Results

Variables	Freq. work from home		Main food shopping method is online		Freq. food delivery		Freq. goods delivery	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constants	-1.129	-12.90	-2.383	-10.24	-0.708	-8.25	2.060	30.87
Thresholds for frequency indicators								
Less than once a month & less than once a week	0.375	14.63	n/a	n/a	0.544	18.98	1.321	23.16
Less than once a week & weekly	0.741	20.65			1.093	23.65	3.335	37.90
Gender (base: male)								
Female	-0.147	-1.78	0.396	7.50	0.151	2.30		
Presence of children in the household (base: no)								
Yes					0.268	4.52		
Age (base: 17 to 39 years old)								
40 or more					-0.224	-3.81		
Employment status (base: full-time)								
Part-time	-0.246	-2.77						
Employment type (base: employee)								
Self-employed	0.837	6.72						
Household income (base: less than £50,000)								
£50,000 and over			0.428	3.99	0.366	6.07	0.257	4.35
Residential location (base: non-metropolitan area)								
Metropolitan area			-0.233	-6.64				
Latent constructs								
VALSC	0.762	16.13	0.746	3.76	0.480	6.85	1.368	38.08
PALSC								
Recursive Endogenous Effects								
Absence of motorized vehicles in the household			0.266	1.81			0.607	4.88

TABLE 4 Physical Activity Engagement (PAG) Outcome Variable Results

Independent variables (base)	Mandatory activity episodes				Maintenance activity episodes				Discretionary activity episodes				Motorized vehicle availability		Average number of trips per tour		Natural log of average trip distance[1]	
	Number		Avg. duration		Number		Avg. duration		Number		Avg. duration							
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constants	1.512	64.35	1.554	33.46	0.963	19.83	0.660	9.89	1.279	16.59	0.917	16.95	1.698	20.25	0.408	9.41	2.006	59.68
Gender (male)																		
Female							0.343	6.33			-0.091	-1.83						
Presence of children in the household (no children)																		
Children															0.254	5.29	-0.338	-4.72
Gender and presence of children (male or female without children)																		
Male with children									-0.361	-3.69								
Female with children	-0.150	-2.73							-0.154	-1.96								
Age (17 to 49 years old)																		
50 or more					0.088	2.29												
Employment status (full-time)																		
Part-time	-0.347	-5.49																
Gender and employment (full-time and part-time male)																		
Part-time female					0.084	2.14												
Full-time female			0.317	7.27											0.115	2.52		
Employment type (employee)																		
Self-employed			-0.742	-8.47														
Household workers (single worker)																		
Multi-worker													0.172	2.88				
Residential location (non-metropolitan)																		
Metropolitan area							0.143	2.73			0.166	2.97	-0.155	-2.25				
Latent constructs																		
VALSC	-0.099	-1.91	-0.063	-1.95	-0.084	-1.97			0.880	20.69			0.388	8.13	0.372	11.97	0.140	7.24
PALSC			-0.108	-3.49			0.064	1.96	-0.239	-2.67	0.082	2.36	-0.952	-20.88	-0.199	-6.49	-0.208	-10.55
Recursive endogenous effects																		
Works from home 1+ times per week			-0.394	-4.12			-0.249	-2.56										
Food delivered 1+ times per week							-0.117	-1.67										
Goods delivered 1+ times per week															-0.269	-5.15		
Total work duration per week (/10)					-0.059	-5.21	-0.076	-5.07	-0.109	-7.07								
Absence of vehicles in the household					-0.468	-5.48			-0.312	-1.87								

[1]Variance of natural logarithm of average trip distance is 0.698 and t-stat is 30.10.

TABLE 5 Treatment Effects Corresponding to Transplanting a Random Individual from One State to Another (stand. err. in parenthesis)

Effect on	ATE corresponding to change from non-telecommuting to telecommuting "one or more times a week"		ATE corresponding to change from <=2 times per year to >=1 times/week for goods delivery frequency	
	GHDM	IHDM	GHDM	IHDM
Number of mandatory activity episodes per week	**0.000**	**-0.650 (0.322)**	0.000	0.000
Average duration of mandatory activity episodes (hours)	**-0.736 (0.224)**	**-0.909 (0.192)**	0.000	0.000
Number of maintenance activity episodes per week	0.000	0.000	**0.000**	**-0.413 (0.063)**
Average duration of maintenance activity episode s (hours)	**-0.127 (0.054)**	**-0.151 (0.054)**	0.000	0.000
Number of discretionary activity episodes per week	0.000	0.000	**0.000**	**-0.265 (0.083)**
Average duration of discretionary activity episodes (hours)	0.000	0.000	0.000	0.000
Average number of trips per tour	0.000	0.000	**-0.087 (0.018)**	**-0.059 (0.011)**

TABLE 6a. Disaggregate Data Fit Measures

(Predictive log-likelihood at constants is -14,797.67; N=3319)

Summary Statistics	Model	
	GHDM	IHDM
Composite marginal log-likelihood value at convergence	-1,058,575	-1,066,129
Composite Likelihood Information Criterion (CLIC)	-1,060,430	-1,067,990
Predictive log-likelihood at convergence	-12,523.98	-13,001.01
Number of parameters	121	125
Predictive adjusted likelihood ratio index	0.147	0.114
Non-nested adjusted likelihood ratio test between the GHDM and IHDM	$\Phi[-30.95] << 0.0001$	

TABLE 6b. Aggregate Data Fit Measures

Alternative comprising working from home <= twice a year and…	Observed Share (%)	GHDM		IHDM	
		Predicted Share (%)	APE* (%)	Predicted Share (%)	APE* (%)
Freq. of food delivery<once a year, # main. episodes=1, # disc. episodes = 0	4.489	3.656	18.556	3.540	21.141
Freq. of food delivery<once a year, # main. episodes=1, # disc. episodes = 1	3.404	3.003	11.780	4.180	22.797
Freq. of food delivery<once a year, # main. episodes=2, # disc. episodes = 0	1.958	2.148	9.704	2.504	27.886
Freq. of food delivery<once a year, # main. episodes=2, # disc. episodes = 1	2.712	2.294	15.413	2.011	25.848
Freq. of food delivery<once a month, # main. episodes=1, # disc. episodes = 0	0.572	0.738	29.021	0.751	31.294
Freq. of food delivery<once a month, # main. episodes=1, # disc. episodes = 1	0.572	0.755	31.993	0.700	22.378
Freq. of food delivery<once a month, # main. episodes=2, # disc. episodes = 0	0.241	0.339	40.664	0.376	56.017
Freq. of food delivery<once a month, # main. episodes=2, # disc. episodes = 1	0.422	0.299	29.147	0.250	40.758
Average APE across all combinations		23.285		31.015	

*APE: Absolute Percentage Error