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Impacts of teleworking and online shopping on travel: a tour-based analysis

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Abstract

Large-scale adoption of telemobility, such as teleworking and online shopping, has affected travel patterns significantly. The impacts of teleworking and online shopping on travel have been studied separately and with trip-level analyses, thereby ignoring tour complexity, trip chaining, and activity scheduling. We aim to address this gap by investigating the interactions between online shopping, teleworking, and travel at a tour level, considering trip chaining and the importance of the activities involved. We classify tours into mandatory (e.g., travel for work, school), maintenance (e.g., travel for grocery shopping, appointments, errands), and discretionary (e.g., travel for non-grocery shopping, leisure, religious activities) tours according to the primary activity purpose. We then estimate a structural equation model using a one-week activity-travel diary from the 2019 Puget Sound Regional Travel Study. The results indicate that teleworking reduced mandatory and maintenance tours while increasing online shopping. Mandatory tours were negatively associated with both maintenance tours and online shopping, whereas the number of maintenance tours was positively associated with the number of discretionary tours. We did not find a statistically significant relationship between online shopping, maintenance tours, and discretionary tours. Overall, this study offers new insights into the effect of teleworking and online shopping on travel, with potential implications for travel demand modeling and management, as well as for the design of travel surveys that take such virtual activities into account.

Keywords Travel behavior · Tour-based model · Information and communication technology (ICT) · Telemobility · Structural equation model · Survey methods

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Introduction

Telemobility eases spatial and temporal constraints on socio-economic activity participation, as activities that previously required traveling, such as working, shopping, healthcare, and schooling, can instead be performed virtually. Even before the COVID-19 pandemic, large-scale adoption of information and communication technologies (ICT) resulted in some types of telemobility, such as teleworking and online shopping (*or e-shopping*), having a considerable impact on mobility patterns and travel behavior (Choo and Mokhtarian 2007; Le et al. 2022; Rotem-Mindali and Weltevreden 2013). Hence, to gain a complete understanding of activity patterns, one cannot separate physical and virtual activities as they are intertwined.

Physical travel is largely a derived demand that depends on the locations of successive scheduled activities. Attributes such as activity type (i.e., trip purpose), duration, destination, time of day, and travel mode directly affect activity-travel planning. Based on these attributes, activities can be classified as "*mandatory*" (i.e., non-negotiable activities such as work, school, picking up/dropping off someone), "*maintenance*" (i.e., less-negotiable activities: grocery shopping, personal business, appointments, errands), and "*discretionary*" activities (i.e., negotiable activities: entertainment, social, recreational, religious, non-grocery shopping) (Ortúzar and Willumsen, 2011).

While most prior studies on ICT and travel assessed either the impact of teleworking on travel or the impact of online shopping on travel, they did not consider these impacts simultaneously. Simultaneous assessments of the relationship between online shopping, teleworking, and travel are becoming increasingly important as rapidly evolving technology and increased Internet access are making teleworking and online shopping more accessible and transforming daily travel-activity patterns. Yet to date, only few studies have explored this interrelationship. Özbilen et al. (2021) studied the relationship between ICT use (online shopping and teleworking) and travel time expenditures by different travel modes. Furthermore, most prior studies explored the impact of ICT use on travel without considering interdependencies between activities conducted during the same tour. This ignores the fact that many trip attributes, such as destination, time of travel, and transportation mode, depend on the tour within which this trip is being chained (Bowman and Ben-Akiva 2001; Ye et al. 2007). As a result, research has generally ignored space–time constraints due to activity scheduling and complex tour forming behavior. This leaves open the question of how various types of telemobility interact with physical mobility to form complex activity-travel patterns.

Our study addresses these gaps by analyzing home-to-home tours that we classify according to the purpose of the primary activity, i.e., as mandatory, maintenance, and discretionary tours. We employ the 2019 Puget Sound Regional Travel Study dataset, a household travel survey with a one-week activity-travel diary that allows us to comprehensively test the intricate relationship between teleworking, online shopping, and travel. Our study extends the literature in ICT and travel as well as tour complexity by considering trip chaining and hierarchy of activity importance. Insights from this study may support practitioners and researchers in the modeling and forecasting of travel behavior and travel demand considering the interactions of physical mobility with telemobility.

This paper is organized as follows: Section Literature review discusses the literature on teleworking, online shopping, and their relationship with travel. Sections Objectives and Methods present the study objectives and methodology. The last two sections discuss the model results, key conclusions, and implications.

Literature review

The relationship between ICT use and travel has been studied extensively (Cao 2009; Gössling 2018; Le et al. 2022). These studies mainly focused on the trip level and relate to either online shopping or teleworking, but not both. Moreover, ICT use in the form of social media has also been found to affect travel for social activities, such as face-to-face social interaction or leisure activities (Calastri et al. 2017; Delbosc and Mokhtarian 2018; van der Waerden et al. 2019). Given the focus of this study, in this section, we review the literature examining the impact of online shopping and teleworking on travel as well as literature on tour-based travel.

Relationship between ICT and travel: the four effects

Numerous studies have found that ICT use significantly alters the way people fulfill their activity and travel needs (Cao 2009; Gössling 2018; Le et al. 2022; Suel and Polak 2018). The literature has identified four possible types of effects of ICT use on travel, namely, complementarity, substitution, modification, and neutrality (Mokhtarian 2002). *Substitution* refers to a net reduction in physical travel due to the use of ICT, whereas *complementarity* implies a generation of physical travel due to ICT use. Salomon (1986, 1985) and Mokhtarian (1990, 1988) were the first to describe these effects. Salomon also introduced the *modification* effect, which refers to changes in one or more travel variables, such as destination, travel mode, or travel distance due to the use of ICT (Salomon 1985). Lastly, the *neutrality* effect occurs when there is no relationship between ICT use and travel, as discussed by Mokhtarian (1990) and Salomon (1985). Mokhtarian et al. (2006) noted the possible coexistence of these four types of effects. For instance, the complementarity and substitution effects of ICT use on travel can coexist at an individual level (Konrad and Wittowsky 2018; Zhang et al. 2007). Other than these four effects, a few studies have identified the presence of a so-called *rebound effect* (Kim 2017; Kim et al. 2015), referring to additional demand for travel generated due to travel time savings from ICT use for unrelated purposes, as further discussed in Sect. Relationship between teleworking and travel.

Relationship between online shopping and travel

The literature on the relationship between online shopping and travel builds on the more general literature covering ICT use and travel. In exploring the effects of online shopping on in-store shopping trips, many researchers have reported one or more of the effects introduced above, with the substitution effect and complementarity effect being the most common ones (Le et al. 2022). The type of effect found tends to vary by study design and measurements of travel outcomes. For instance, several studies in China and Europe using longitudinal or quasi-longitudinal surveys found the presence of substitution effects (Suel et al. 2018; Suel and Polak 2017; Weltevreden and Rietbergen 2009; Xi et al. 2020b), while other studies that reported complementarity effects mostly used cross-sectional data (Cao 2012; Lee et al. 2017). One study (Bhat et al. 2003) with longitudinal data also found a combination of the two effects (i.e., substitution and complementarity). A few studies found modification effects (Shi et al. 2020a, 2020b) when measuring changes in travel distances of online shoppers. Some studies also indicated the co-presence of multiple effects, such as complementarity and substitution (Etminani-Ghasrodashti and Hamidi 2020; Farag et al. 2007). Despite a large number of studies, there is currently no consensus regarding the dominant type of effect of online shopping on shopping travel.

Most studies considered individual shopping trips and did not explore the trip chaining aspect of travel. Le et al. (2022) noted that trip characteristics, Internet experience and access, household structure, delivery characteristics, and socio-demographics are primary determinants of the choice between shopping in-store and shopping online. Furthermore, they also concluded that past literature had extensively relied on one-day travel survey data to analyze the impact of ICT use on travel. However, as shopping activities do not occur on a daily basis, using one-day travel diary data and cross-sectional surveys might not provide a full picture of shoppers' behavior. Thus, the findings of many studies may have been impacted by data limitations.

Relationship between teleworking and travel

Teleworking, or telecommuting, allows workers to work from a location of their choice rather than a central workplace. In the 1970s, researchers began considering teleworking a possible net substitution to the work commute (Nilles et al. 1976) and a means to reduce travel and air pollution (Handy and Mokhtarian 1996; Salomon 1998). Recent studies provided empirical evidence for a substitution effect of teleworking on commute trips (Elldér, 2020; Helminen and Ristimäki 2007).

However, teleworking may not result in a net reduction in travel in all cases. The ability to telecommute on some days and work at the office other days may lead individuals to live farther away from their workplace, thereby potentially increasing the total distance traveled for commuting purposes. Furthermore, the presence of a rebound effect with teleworking has also been detected, where a teleworker reduces their work-related commute travel but instead engages in additional travel for other purposes, e.g., for leisure purposes (Kim 2017; Kim et al. 2015). In some cases, this additional travel may be due to reallocation of time saved from commuting to other activities. Asgari et al. (2016) found an increase in both nonmandatory activity duration and total daily trip rates for telecommuters. Thus, the total distance traveled per week by teleworkers in comparison to non-teleworkers may be greater, and some studies have shown a (net) complementarity effect between teleworking and overall travel (Choo and Mokhtarian 2007; Silva and Melo 2018; Zhu et al. 2018). Özbilen et al. (2021) found that teleworking reduced the use of motorized modes of travel, i.e., car and transit. Overall, the rebound effect can be considered as a special case of the modification effect (Le et al. 2022) and in the case of some outcome variables can also involve a complementarity effect.

Previous studies mostly analyzed the effects of teleworking and online shopping on travel separately. However, some individuals may engage in both online shopping and teleworking, especially with rapidly evolving technology and increased Internet access. Hence, simultaneous assessments of the relationship between online shopping, teleworking, and travel are extremely important, but such assessments have hardly been conducted to date (Özbilen et al. 2021). Analyzing the relationship between online shopping and teleworking simultaneously can provide a more comprehensive picture of the interactions between ICT use and travel.

Tour-based activity-travel behavior

The literature has classified tour-forming behavior by the complexity of a tour (Daisy et al. 2018; Schneider et al. 2021; Ye et al. 2007) or the purpose of a primary activity of a tour (Bowman and Ben-Akiva 2001; Golob 2000; Ortúzar and Willumsen, 2011). For instance, Bowman and Ben-Akiva (2001) presented an activity-based travel demand modeling system to capture space–time constraints of activities in a tour in which they defined tour complexity as the number of trips in each tour while also classifying tours based on the primary activity.

One of the reasons that studies classified tours based on their complexity was to detect relationships between mode choice and trip chaining (Daisy et al. 2018; Schneider et al. 2021; Ye et al. 2007). For example, Ye et al. (2007) found that mode choice depends on the tour complexity and trip purpose. In a study in Norway, Vågane (2012) found that individuals are likely to chain non-work trips with work travel during weekdays, and that the complexity of tours depends on family structure. Lee and McNally (2006) found that individuals plan their daily tours based on the importance level of each activity. Moreover, if an opportunity presents itself, they might chain trips with lower priority to previously planned anchored trips (i.e., the most important or prioritized trip with an extended activity duration).

Objectives

While researchers have found that tour complexity and activity scheduling are important variables when analyzing daily travel, as noted in the literature review, most studies on the impact of online shopping and teleworking on travel were conducted as trip-level analyses, thereby ignoring these complexities. Moreover, there is a lack of consensus regarding the impact of online shopping and teleworking on travel in the literature, likely due to different survey designs, including but not limited to aspects such as sampling methods, the cross-sectional or longitudinal nature of the survey, or the presence and length of a travel diary (Le et al. 2022; Xi et al. 2020a). Our study seeks to address some of these issues by (1) simultaneously quantifying the relationship between online shopping, teleworking, and tour-forming behavior while considering the importance of the activities involved; and (2) analyzing the impact of the length of the survey period on the relationship between ICT use and travel in the Puget Sound data set. The second analysis serves to understand the sensitivity of our results to the tracking period and to support future researchers seeking to determine an appropriate tracking period for a study on ICT use and travel.

Methods

We used data from the 2019 Puget Sound Regional Household Travel Survey, which collected an activity-travel diary, socio-demographic information, and socio-economic information at both the individual and the household level (Puget Sound Regional Council 2020). The survey was conducted in four counties of the central Puget Sound region in the US state of Washington, namely, King, Pierce, Kitsap, and Snohomish counties, between April and June 2019. Traditional address-based sampling was used to select households and mail invitations to participate in the study.

Invited households completed an initial recruitment screening through the study website or by phone. Based on their responses regarding smartphone ownership in the recruitment screening, all individuals from selected households were invited to complete either a one-day or a one-week activity-travel diary. That is, if all individuals in the household owned a smartphone less than four years old and agreed to participate in the one-week travel diary collection, they were invited to do so. Households that completed the one-day activity-travel diary were assigned to a Tuesday, Wednesday, or Thursday as the day on which they completed the diary (the "travel day"), whereas households completing the one-week activity-travel diary were assigned Tuesday as first day of the diary. Households reported their activity-travel diaries through the *rMove* smartphone app or, if not all household members owned smartphones less than four years old, a web-based survey. The study collected telemobility information, such as the amount of telework time, online shopping time, and information about deliveries of goods purchased online on each day surveyed, separately for all members of household. Compared to other regional or national travel surveys in the US, the Puget Sound data set is unique in its detailed information on telemobility as well as the long tracking duration for all individuals in the households selected for the one-week travel-activity diary. This allows us to capture behavior that cannot be observed in a one-day diary (Le et al. 2022). In this study, we use the one-week activity-travel diary data to explore the relationship between telemobility and travel.

Data processing

The original sample includes 801 individuals from 595 households who completed the one-week activity-travel diary. We removed data from participants who did not provide information on their online shopping, teleworking duration, or online delivery (n = 113 people). Moreover, as we focus on the interactions between online shopping, teleworking, and travel, we also removed individuals who reported that they spent no time shopping online and no time teleworking during the survey week (n = 143 people). As individuals within the second group may have been subject to unobserved constraints that did not allow them to perform online activities (e.g., not allowed to work from home, no access to a credit card), this prevented the introduction of a bias due to the unobserved constraints. Therefore, the final data set includes one-week activity-travel diaries of 545 individuals from 470 households. We performed the analysis at the individual level and did not account for the interactions between individuals of the same household.

We defined a tour as a combination of trips that originated from home and ended at home. We discarded tours that did not begin or end at home, consistent with the tour definition proposed by Primerano et al. (2008). As a result, we removed 393 trips out of a total of 22,818 trips that were not part of tours that started and ended at home during the survey period. Out of the 393 discarded trips, 99 were for mandatory purposes, 31 for maintenance purposes, 204 for discretionary purposes, and 59 were trips to home. We did not remove any non-home-based sub-tours that were embedded into home-based tours. We classified tours into three categories, namely mandatory tours, maintenance tours, and discretionary tours, based on the type of primary activity undertaken during the tour. A mandatory tour contains at least one mandatory activity (e.g., work, school, pick up/drop off someone) and might contain additional maintenance and discretionary activities. A maintenance tour contains a maintenance activity as the primary purpose (e.g., grocery shopping, personal business, appointment, errands) and does not contain any mandatory activity. It may also include discretionary activities. Lastly, a discretionary tour only contains one or more discretionary activities (e.g., entertainment, social, recreational, religious activity, shopping in a mall), and does not include any mandatory or maintenance activities. For example, a tour composed of “Home → Work → Errands → Social activities → Home” would be classified as a mandatory tour since work is the primary activity. A tour composed of “Home → Personal business → Religious activity → Home” would be classified as a maintenance tour since personal business and the religious activity are the primary activities, whereas a tour composed of “Home → Entertainment → Eating out → Home” would be classified as a discretionary tour.

We performed the analysis at an individual level and aggregated all variables from the travel-activity diary over the full week to capture the impact across all travel reported in the seven-day activity-travel diary. For each type of tour, we calculated the total number of trips, total travel time, and percentage of chained vehicle miles traveled (VMT). For example, for a given individual’s mandatory tours, the percentage of chained mandatory VMT is calculated by summing the VMT of all chained mandatory tours (tours with more than one activity) and dividing that by the total VMT of all mandatory tours. We aggregated online shopping time over the week and counted the number of days on which a person received package deliveries and other deliveries (i.e., groceries and food). The Puget Sound data set does not include the total number of individual deliveries, only the number of days on which a delivery was received. Given the data aggregation over the week, our study is cross-sectional.

We motivated this study by observing that trip-level analyses ignore the complexities of tours and may yield different results than tour-level analyses. Recognizing that a tour-based analysis is complex, and its results may depend on the tour classification and travel outcome variables, we took further steps to address these issues. First, we chose a classification based on the primary activity conducted in the tour, following a hierarchy of activity purposes. By doing so we can capture the scheduling of tours based on the importance of the activities involved. Second, our analysis accounts for multiple outcome variables simultaneously by using a latent variable model, thus capturing a more holistic view of the interactions between ICT use and travel. This helps overcome the limitations of prior studies that reached contradictory conclusions due to their reliance on single travel outcomes.

Model specification and analysis approach

We used structural equation modeling (SEM) to analyze the relationship between telework, online shopping, and travel behavior. A full-scale SEM model has two components, the structural model and the measurement model. It can include both latent and observed variables as dependent (endogenous) and independent (exogenous) variables. The structural model depicts the relationships between exogenous and endogenous variables and between different endogenous variables. Since latent variables are unobserved, a set of observed variables (indicators) is used in the measurement model to identify a latent variable. Equations (1, 2 and 3) show the basic structure of an SEM model in standard matrix notation (Kline 2015). Equations (1 and 2) are measurement models for latent exogenous and endogenous variables, and Eq. (3) represents the structural model.

$$\boldsymbol{x} = \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta} \tag{1}$$

$$\boldsymbol{y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{2}$$

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{3}$$

where: $\boldsymbol{x}$: $(m \times 1)$ vector of observed exogeneous variables, $\boldsymbol{y}$: $(n \times 1)$ vector of observed endogenous variables, $\boldsymbol{\xi}$: $(p \times 1)$ vector of latent exogenous variables, $\boldsymbol{\eta}$: $(q \times 1)$ vector of latent endogenous variables, $\boldsymbol{\Lambda}_x$: $(m\ x\ p)$ matrix of the effect of latent exogenous variables on the observed exogenous variables, $\boldsymbol{\Lambda}_y$: $(n\ x\ q)$ matrix of the effect of latent endogenous variables on the observed endogenous variables, $\mathbf{B}$, $\boldsymbol{\Gamma}$: $(q\ x\ q)$ matrix (for latent endogenous variables) and $(q\ x\ p)$ matrix (for latent exogenous variables) of coefficients, $\boldsymbol{\delta}, \boldsymbol{\varepsilon}, \boldsymbol{\zeta}$: $(m \times 1)$, $(n \times 1)$, and $(q \times 1)$ vectors of errors.

In addition to direct effects, SEM can also measure indirect effects between variables. The sum of the direct and indirect effects between a pair of variables is known as the total effect between them. In an SEM model, if variable X affects variable Y, then the path (X→Y) represents the direct effect of X on Y. Furthermore, if variable Y affects variable Z, then the path (X→Y→Z) is the indirect effect of X on Z.

Figure 1 shows the hypothesized relationships between the endogenous variables representing travel, teleworking, and online shopping. Based on prior literature, we hypothesize that (i) teleworking duration affects all three tour types and online shopping behavior, (ii) online shopping behavior affects maintenance and discretionary tours, (iii) mandatory tours affect maintenance and online shopping behavior, (iv) maintenance tours affect discretionary tours, and (v) socio-demographic variables (exogenous variables) affect all five endogenous variables. The hypothesized relationships between tour types, shown here as arrows, are derived from the literature (Bowman and Ben-Akiva 2001; Ortúzar and Willumsen 2011; Singleton 2013) and represent the way travelers are assumed to plan their daily activities (Bowman and Ben-Akiva 2001): individuals first plan mandatory tours, which are more constrained than the other two types, before scheduling maintenance and discretionary tours. Given that mandatory tours have the least flexibility, we hypothesize that they also affect online shopping behavior, which is often a maintenance activity and is more negotiable than mandatory activities. Furthermore, online shopping may affect maintenance and discretionary tours that contain shopping trips since such tours can also contain other non-shopping activities. Given the interactions of online and in-store shopping activities, the scheduling of other non-mandatory activities may be modified. A large body of literature has found a substitution effect of online shopping on shopping trips (Le et al. 2022; Suel et al. 2018; Suel and Polak 2017; Weltevreden and Rietbergen 2009; Xi et al.

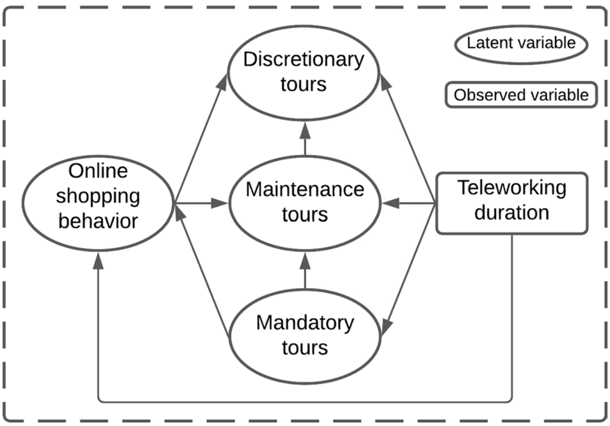

Fig. 1 Conceptual relationships between online shopping, telework, and travel (endogenous variables)

2020b), therefore a reduction in shopping travel would impact other maintenance or discretionary activities that could have been chained with shopping trips.

Online shopping behavior, mandatory tours, maintenance tours, and discretionary tours were defined as latent endogenous variables that were measured using observed indicator variables in the measurement model. For each tour-related latent variable, the indicators were the total number of trips in all respective tours, total travel time, and percent of chained VMT. The latent variables capture the respondent's tour-based travel behavior, measured along several dimensions, and classified according to the primary activity conducted during the tour. Online shopping was measured using total time spent shopping online, the number of days on which package deliveries were received, and the number of days on which other deliveries (i.e., grocery, and food) were received. Teleworking was measured by the total time spent teleworking during the week.

We estimated the SEM model using the general analysis and maximum likelihood robust (MLR) estimators in Mplus 8.4 (Muthén and Muthén, 2017). As some of the continuous variables were non-normal and some dummy variables were included in the structural part, we selected MLR to generate parameter estimates and standard errors that are robust to non-normality. We first ensured that the relationship between the latent variables and their observed indicators in the measurement model fit properly using confirmatory factor analysis (CFA) (Jöreskog et al. 2016). After that, we identified significant demographic variables in the structural part of the SEM model. We employed the nonparametric bootstrapping method (Preacher and Hayes 2008), which does not assume normality, to estimate the standard errors (S.E.) and perform significance testing for all indirect effects (mediation effects) and total effects. We used 10,000 bootstrap draws to estimate the standard errors and p-values of indirect and total effects.

To better understand the impact of the tour-based analysis and the use of multiple outcome variables, we also conducted a comparative analysis, where we estimated additional models with the same structure and addressing the same research question as the model shown in Fig. 1, but using different outcome variables. Namely, we specified a trip-based latent variable model as well as two sets (one tour-based and one trip-based) of three single-indicator models, each using one of the three indicator variables as the travel outcome instead of a latent variable. For example, one of the models used the number of trips by purpose in lieu of the latent variables. As the comparative analysis is not the core focus of this paper, details are provided in the appendix.

Assessing the impact of travel survey design on the ICT–travel relationship

To analyze the impact of the length of the survey period on the relationship between ICT use and travel, we created two pseudo one-day travel-activity diaries from the one-week diary data with 545 individuals from 470 households. In the first pseudo one-day diary (Sample I), all 470 households were randomly assigned to either Tuesday, Wednesday, or Thursday as the travel day, with equal probability of travel day assignment. This assignment method mimics the one-day travel diary collection method used in the Puget Sound survey. In the second pseudo diary (Sample II), households were randomly assigned to one of the seven days of the week as their travel day, with equal probability of assignment. This assignment mimics the one-day travel diary collection method used in the 2017 National Household Travel Survey (Federal Highway Administration 2017). For both samples, we extracted the activity and travel information on the assigned travel day, thus creating pseudo one-day travel-activity diaries of the same 545 individuals as we had in the one-week travel-activity diary.

We estimated SEM models using the specification introduced in Sect. Model specification and analysis approach for both pseudo one-day travel diaries. That is, we followed the same data aggregation and modeling approach as with the one-week data, albeit using the one-day activity and travel data.

Results

This section discusses the descriptive statistics of the final sample. We present the results for the relationship between online shopping, teleworking, and tour complexity modeled using the one-week travel data set. Then, we assess the results for the one-day travel data to demonstrate the potential pitfalls of using one-day travel diaries in studying ICT use and travel.

Descriptive statistics

Table 1 shows the descriptive statistics of the final sample of 545 individuals from 470 households. Statistics on travel and ICT use are reported based on the one-week activity-travel diary. The modes were respondents 18–34 years of age, working full time, having a bachelor's degree, and earning more than $100,000 at the household level. The mean household size was 2.1, with an average of 1.7 adults and 1.4 workers in the household. One-adult households accounted for 30.9% of the sample, and households without a motor vehicle accounted for 22.8%. On average, individuals spent 534 min per week teleworking and 117 min shopping online, and received package deliveries and other deliveries (i.e., groceries and food) on 1.64 days and 0.35 days of the week, respectively.

Also shown in Table 1 are the descriptive statistics for the original sample, including all individuals who completed the one-week activity-travel diary in the Puget Sound Regional Household Travel Survey, and for the population of the central Puget Sound region, based on the American Community Survey (ACS) 2016–2020 5-year estimates (U.S. Census Bureau 2020). A comparison between the final sample after data cleaning (see Sect. Data processing) and the original sample indicates that the data processing had minimal impact on the distribution of demographics. A comparison between the original sample and the ACS 2016–2020 data shows a similar distribution of the household income, household size, and gender variables, but there are considerable differences for vehicle ownership and age. These may be due to differences in the survey design and sampling method.

Modeling the relationship between ICT use and tour complexity

Table 2 shows the goodness-of-fit statistics of the SEM model based on the one-week travel and ICT use data and with the model structure presented in Sect. Model specification and analysis approach. All indicators suggest that the model is a good fit according to the guidelines of Hu and Bentler (1999). The CFI values range from 0 to 1, where 1 is the best model fit. The CFI estimates the deviation of the researcher's model from a perfect fit while comparing it against a null model (Kline 2015). The RMSEA and SRMR are absolute metrics that indicate how far the model is from a perfect fit, which is at 0. An RMSEA value below 0.05 indicates a good fit in terms of the (co)variance in the data explained by

Table 1 Descriptive statistics

Variables	Final Sample Percentage/Mean (S.D.)	Original Sample Percentage/Mean (S.D.)	ACS 2016–2020 Percentage/Mean
Number of Households	470	595	1,635,633
Number of Individuals	545	801	4,197,443
Household-level variables			
Household income			
Under $25,000	7.2%	7.9%	12.2%
$25,000-$49,999	11.5%	13.8%	15.6%
$50,000-$74,999	12.3%	12.8%	15.8%
$75,000-$99,999	13.6%	13.6%	13.4%
$100,000 or more	51.5%	47.9%	42.9%
Prefer not to answer	3.8%	4.0%	–
Household size	2.1 (1.1)	2.1 (1.1)	2.5
Number of adults	1.7 (0.6)	1.71 (0.6)	
Number of children	0.4 (0.8)	0.4 (0.9)	
Number of workers	1.4 (0.7)	1.4 (0.7)	
One-adult household	30.9%	31.6%	
Vehicle ownership			
0	22.8%	21.5%	8.0%
1	43.4%	45.7%	30.9%
2	28.1%	26.7%	37.2%
3+	5.7%	6.1%	23.8%
Individual-level variables			
Age			
Under 18 years	0.0%	9.4%	21.5%
18–34 years	45.3%	41.6%	25.1%
35–54 years	39.5%	34.3%	27.5%
55–74 years	13.4%	13.0%	20.6%
75 years or more	1.84%	1.8%	5.2%
Gender: Male	46.6%	47.4%	50.1%
Employment			
Working full-time	67.2%	58.1%	
Working part-time	7.3%	7.6%	
Working, self-employed	7.2%	5.9%	
Retired	7.3%	7.9%	
Unemployed	6.1%	5.9%	
Other	5.0%	14.7%	
Education*			
Less than high school	0.7%	0.7%	7.0%
High school graduate	2.2%	4.0%	19.3%
Some college	9.0%	9.7%	30.7%#
Vocational/technical training	2.0%	2.3%	
Associate degree	6.1%	5.6%	
Bachelor's degree	45.3%	39.2%	26.5%
Graduate/post-graduate degree	34.7%	29.1%	16.5%

Table 1 (continued)

Variables	Final Sample Percentage/Mean (S.D.)	Original Sample Percentage/Mean (S.D.)	ACS 2016–2020 Percentage/Mean
Not available: Missing	–	9.4%	–
Variables related to travel and ICT use			
Mandatory tours			
Number of trips in a week	14.4 (12)		
Travel time in a week (minutes)	296.0 (311.5)		
Percentage of chained VMT	59 (38)		
Maintenance tours			
Number of trips in a week	5.0 (5.3)		
Travel time in a week (minutes)	71.6 (109.3)		
Percentage of chained VMT			
Discretionary tours			
Number of trips in a week	10.65 (8.93)		
Travel time in a week (minutes)	185.69 (194.4)		
Percentage of chained VMT	43 (38)		
Online shopping behavior			
Online shopping time	116.6 (164.6)		
Number of days when package received	1.6 (1.7)		
Number of days when other delivery received	0.4 (0.8)		
Teleworking duration in a week (minutes)	534.3 (777.4)		

**ACS 2016–2020 reported educational attainment only for the population aged 25 years and over*

#ACS 2016–2020 did not report values for the "vocational/technical training" and "associate degree" categories, thus we assumed that the "some college" category included these two categories

Table 2 Model goodness-of-fit statistics

Goodness-of-fit statistic	Standard	Estimated value
Degrees of freedom (d.f.)	The greater, the better	236
χ^2	The smaller, the better[a]	366.192
Relative chi-square: χ^2/d.f	< 3: good fit, < 5: fair fit	1.55
Comparative fit index (CFI)	The greater, the better	0.927
RMSEA (Root Mean Square Error of Approximation)	< 0.05: good fit, < 0.08: fair fit	0.032
90% confidence interval for RMSEA		[0.026, 0.039]
SRMR (standardized root mean square residual)		0.043

[a] χ^2 is not a good measure of goodness of fit, as it increases with sample size

the model, whereas an SRMR value below 0.05 indicates that not much (co)variance is left unexplained in the model (Kline 2015).

Table 3 show the standardized coefficients of indicators for the latent variables (from the measurement model) and Table 4 show the direct and total effects of both

Table 3 Measurement model with standardized coefficient estimates *(n = 545)*

Variables	Estimate	S.E	p-value
Mandatory tours			
Travel time	0.714	0.068	< 0.001
No. of trips	0.937	0.025	< 0.001
Percentage of chained VMT	0.609	0.043	< 0.001
Maintenance tours			
Travel time	0.787	0.048	< 0.001
No. of trips	0.994	0.028	< 0.001
Percentage of chained VMT	0.601	0.035	< 0.001
Discretionary tours			
Travel time	0.710	0.061	< 0.001
No. of trips	0.988	0.044	< 0.001
Percentage of chained VMT	0.361	0.040	< 0.001
Online shopping			
Online shopping time	0.589	0.077	< 0.001
Package deliveries	0.455	0.050	< 0.001
Other deliveries	0.464	0.044	< 0.001

endogenous and exogenous variables on endogenous variables. At a significance level of 0.05, all indicator estimates in the measurement model (Table 3) are greater than the threshold value of 0.3 (Xi et al. 2020b).

The structural model results represent the relationships between teleworking, online shopping, and travel behavior. Teleworking time reduced the tendency to make mandatory tours ($\widehat{\beta}$ = −0.201) and maintenance tours ($\widehat{\beta}$ = -0.068), controlling for socio-demographics. However, teleworking time indirectly increased online shopping ($\widehat{\beta}$ = 0.055). If teleworking duration increased by one standard deviation, the number of mandatory tours would decrease by 0.201 standard deviations and online shopping behavior would increase by 0.055 standard deviations through the total effects. Making mandatory tours also reduced the tendency to make maintenance tours and to shop online. Conversely, making maintenance tours increased the tendency to make discretionary tours. The model does not show any statistically significant effects of online shopping on maintenance and discretionary tours, or of teleworking on discretionary tours. Figure 2 depicts the relationships (direct effects) between the endogenous variables.

We found several socio-demographic factors that affect telemobility. Specifically, households without a vehicle made fewer maintenance and discretionary tours ($p < 0.05$). Households with more children made more mandatory tours and did less teleworking. Individuals with graduate/post-graduate degrees spent more time teleworking and performed fewer mandatory tours. People from households in the highest income brackets (i.e., more than $100,000 per year) tended to telework more than households with incomes between $25,000 and $74,999. Individuals from single-adult households shopped online less than other those from other types of households. Compared to self-employed individuals, full-time employees teleworked and traveled more for mandatory tours, but they made fewer maintenance and discretionary tours and also performed less online shopping. Working part-time also to an increase in mandatory tours and hence indirectly reduced maintenance tours and online shopping behavior. Adults in the 18–54 age group teleworked more than individuals of age 55 or more. Moreover, individuals

Table 4 Structural model with standardized coefficient estimates ($n = 545$)

Variables	Direct effect	S.E. (Direct effect)	Total effect
Endogenous variables			
Telework duration → Mandatory tours	– 0.201 **	0.038	– 0.201 **
Telework duration → Maintenance tours	– 0.093 **	0.042	– 0.068 *
Telework duration → Discretionary tours	0.014	0.041	0.005
Telework duration → Online shopping	– 0.041	0.063	0.055 **[3]
Online shopping → Maintenance tours	0.014	0.076	0.014
Online shopping → Discretionary tours	– 0.037	0.065	– 0.035
Mandatory tours → Online shopping	– 0.273 **	0.063	– 0.273 **
Mandatory tours → Maintenance tours	– 0.123 **	0.043	– 0.127 **
Mandatory tours → Discretionary tours	–	–	– 0.015 *
Maintenance tours → Discretionary tours	0.119 **	0.052	0.119 **
Exogenous variables			
No vehicle ownership *(dummy var.)* → Maintenance tours	– 0.104 **	0.039	– 0.104 **
No vehicle ownership *(dummy var.)* → Discretionary tours	– 0.122 **	0.042	– 0.134 **
Household income \$25 K-\$49.9 K *(Ref: Household income more than \$100 K)* → Telework duration	– 0.065 *	0.040	– 0.065 *
Household income \$50 K-\$74.9 K *(Ref: Household income more than \$100 K)* → Telework duration	– 0.074 **	0.038	– 0.074 **
Household income \$50 K-\$74.9 K *(Ref: Household income more than \$100 K)* → Mandatory tours	0.000	–	0.015 *
1-adult household *(dummy var.)* → Online shopping	– 0.156 **	0.070	– 0.156 **
Number of kids in the household → Mandatory tours	0.184 **	0.062	0.201 **
Number of kids in the household → Maintenance tours	0.000	–	– 0.023 **
Number of kids in the household → Online shopping	0.000	–	– 0.051 **
Number of kids in the household → Telework duration	– 0.084 **	0.038	– 0.084 **
Graduate/post-graduate degree *(dummy var.)* → Telework duration	0.089 **	0.043	0.089 **
Graduate/post-graduate degree *(dummy var.)* → Mandatory tours	0.000	–	– 0.018 *
Working full-time *(Ref: Working self-employed)* → Mandatory tours	0.370 **	0.056	0.343 **
Working full-time *(Ref: Working self-employed)* → Maintenance tours	0.000	–	– 0.056 **
Working full-time *(Ref: Working self-employed)* → Discretionary tours	– 0.190 **	0.049	– 0.191 **
Working full-time *(Ref: Working self-employed)* → Online shopping	0.000	–	– 0.099 **
Working full-time *(Ref: Working self-employed)* → Telework duration	0.136 **	0.045	0.136 **
Working part-time *(Ref: Working self-employed)* → Mandatory tours	0.205 **	0.047	0.205 **
Working part-time *(Ref: Working self-employed)* → Maintenance tours	0.000	–	-0.026 **
Working part-time *(Ref: Working self-employed)* → Online shopping	0.000	–	– 0.056 **
Male *(dummy var.)* → Maintenance tours	– 0.087 **	0.041	– 0.087 **
Age 55–74 *(Ref: Age 35–54)* → Online shopping	– 0.192 **	0.055	– 0.192 **
Age 55–74 *(Ref: Age 35–54)* → Telework duration	– 0.087 *	0.046	– 0.087 *
Age 75 + *(Ref: Age 35–54)* → Telework duration	– 0.058 **	0.028	– 0.058 **
Age 55–74 *(Ref: Age 35–54)* → Mandatory tours	– 0.077 *	0.044	– 0.059
Age 75 + *(Ref: Age 35–54)* → Mandatory tours	– 0.075 **	0.025	– 0.063 **

(1) A direct effect of 0.00 in exogeneous variables means that the estimate of the direct effect between variables is insignificant at a significance level of 0.1 and was replaced manually with 0.00

(2) All categories of age and household income variables (shown in Table 1) were included in the model, however, only significant variable categories are reported here

(3) The total effect of teleworking on online shopping doesn't include the direct effect, as the direct effect was insignificant (p-value: 0.8)

(4) Significance level codes: *$0.05 \leq p < 0.1$; **$p < 0.05$

in the 18–54 age group performed more online shopping than individuals of age 55 or more.

As discussed in Sect. Model specification and analysis approach, we estimated several additional models with the same structure and addressing the same research questions as the model shown in Fig. 2, but using different outcome variables and different analysis levels (i.e., trip-based and tour-based analysis). A trip-based latent variable model similar to the tour-based latent variable model shown in Fig. 2 failed to converge. The other two sets of models (one tour-based and one trip-based set) that each contained three single-indicator converged successfully. However, their goodness-of-fit statistics were unsatisfactory, and the tour-based latent variable model remained the best model in terms of fit. Detailed results are presented in the appendix.

Assessment of the impact of travel survey design on the ICT–travel relationship

As discussed in Sect. Assessing the impact of travel survey design on the ICT – travel relationship, we created two pseudo one-day travel diaries from the one-week sample used in our tour-based one-week model. In Sample I, households were randomly assigned with equal probability to either Tuesday, Wednesday, or Thursday as their travel day (i.e., excluding weekend). In Sample II, households were randomly assigned with equal probability to one of the seven days (i.e., including weekend). As these samples were extracted from the one-week activity-travel diary, both have the same socio-demographic characteristics as shown in Table 1. The descriptive statistics of variables related to travel and ICT use can be found in Table 5. On average, Sample I includes more mandatory tours, more teleworking time, and fewer maintenance and discretionary tours than Sample II. This was expected, as Sample I only consisted of weekdays whereas Sample II included all seven days of the week. As Sample I and Sample II were one-day diaries, the two online shopping variables, *package received on travel day* and *other delivery received on a travel day,* effectively became binary variables.

For the analysis of Sample I and Sample II, we used the same model specification and the same individuals as we did with the one-week travel diary data, thus the results are directly comparable (Table 3). Both models converged, however they produced considerably different results than the model based on the one-week travel diary, the results of which are shown in Table 3**.** The model results based on Sample I and Sample II also differ substantially. We observed three notable differences between the tour-based, one-day models and the tour-based, one-week model. First, in both one-day models, some of the indicator estimates in the measurement model did not pass the threshold value of 0.3 (Xi et al. 2020b) at a 0.05 level of significance. Specifically, the online shopping behavior latent variable was poorly quantified by the “package delivery” and “other delivery” indicator variables, as both had very low factor loadings (on average, $\widehat{\beta}_{\text{package\_delivery}} = 0.13$

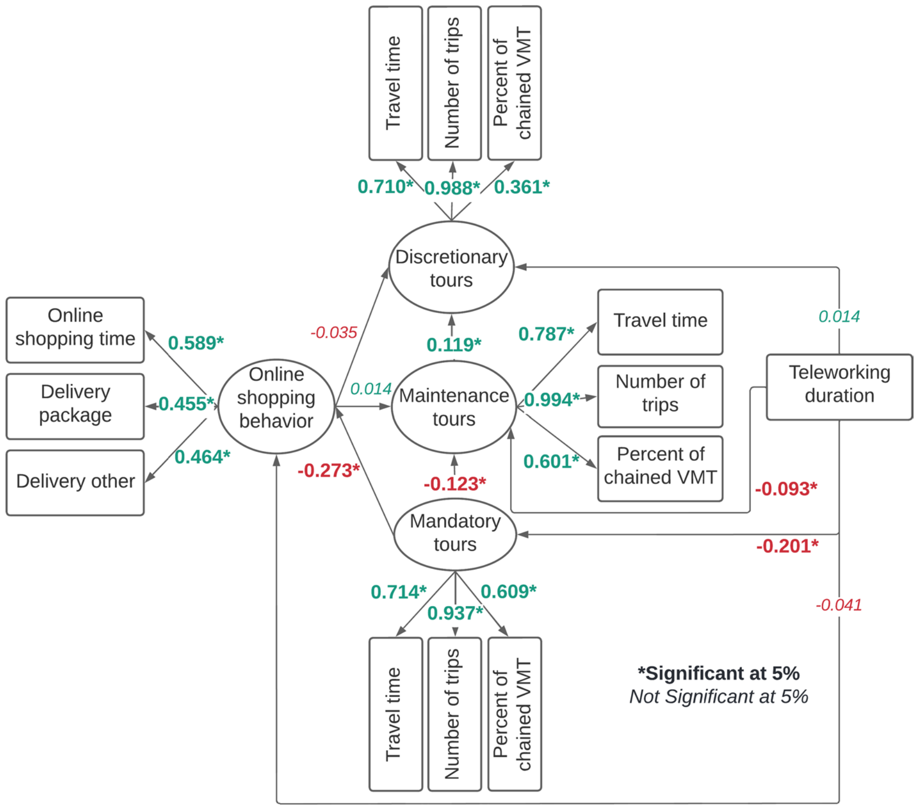

Fig. 2 SEM model results: Direct effects between online shopping, teleworking, and travel

and $\widehat{\beta}_{\text{other\_delivery}} = 0.28$, $p < 0.05$). In the one-week travel diary model, all indicators of all four latent variables (i.e., online shopping behavior, mandatory tours, maintenance tours, and discretionary tours) were significant with factor loadings greater than 0.3. Second, the relationship between maintenance tours and discretionary tours was not significant in the one-day models despite being significant in the tour-based latent variable model. Third, many socio-demographic variables that significantly explained ICT use (i.e., online shopping behavior and teleworking) and discretionary tours in the tour-based, one-week model (Fig. 2) were no longer significant with the one-day diary data.

Discussion

Effects of ICT use on tour complexity and activity scheduling

The tour-level analysis model results show that teleworking is negatively associated with mandatory and maintenance tours and there is no significant effect on discretionary tours. This suggests an overall modification effect, where the specific effect on travel depends on the type of tour. Our observation is consistent with other literature based on trip-level

Table 5 Additional descriptive statistics for pseudo one-day travel diaries (n = 545)

Variables related to travel and ICT use	Sample I		Sample II	
	Mean	Standard deviation	Mean	Standard deviation
Individual-level variables				
Mandatory tours				
Number of trips on a travel day	2.41	2.61	1.98	2.60
Travel time on a travel day (minutes)	49.45	58.70	37.89	54.49
Percentage of chained VMT	39%	48%	33%	47%
Maintenance tours				
Number of trips on a travel day	0.49	1.31	0.68	1.62
Travel time on a travel day (minutes)	6.27	20.01	9.25	27.47
Percentage of chained VMT	8%	27%	12%	32%
Discretionary tours				
Number of trips on a travel day	1.17	1.92	1.49	2.18
Travel time on a travel day (minutes)	17.65	37.3	23.74	44.88
Percentage of chained VMT	14%	34%	15%	34%
Online shopping behavior				
Online shopping time on a travel day	16.05	31.54	16.40	34.86
Package received on travel day (dummy var.)	0.28	0.45	0.28	0.45
Other delivery received on travel day (dummy var.)	0.05	0.21	0.05	0.21
Teleworking duration on a travel day (minutes)	111.1	190.79	75.36	158.04

analyses that found the presence of both substitution and neutrality effects of ICT use on travel (Calderwood and Freathy 2014; Zhai et al. 2017). Our findings also indicate that telework indirectly increases maintenance tours via its effect on mandatory tours. In other words, if the teleworker makes fewer mandatory tours, they will likely make additional separate maintenance tours due to the lack of opportunities to chain maintenance trips with mandatory trips. These results are consistent with prior literature showing that ICT use reduces the number of work trips (i.e., has a substitution effect) (Elldér, 2020; Helminen and Ristimäki 2007) and has a modification effect on non-commute trips (Asgari et al. 2016). Hence, our findings suggest that previously observed effects of teleworking on individual trips are also observable at a tour level.

To the best of our knowledge, this is the first study to establish that teleworking has a positive relationship with online shopping, albeit via an indirect path. We hypothesize that due to reduced travel as a result of teleworking, individuals have fewer opportunities to chain non-mandatory trips with their mandatory trips, which may induce more online shopping. Furthermore, the literature suggests that access to computers and experience with the Internet are significant variables in explaining online shopping behavior (Le et al. 2022). Since these are generally also prerequisites for teleworking, they may catalyze more online shopping.

This study also finds that more mandatory tours result in fewer maintenance tours, whereas maintenance tours generate additional discretionary tours. These results are indicative of complex activity scheduling and tour-forming behavior and suggest that individuals tend to chain non-work trips with work trips. The existence of such chaining behavior is supported by prior literature that also observed a negative association between work tours and non-work tours (Golob 2000; Vågane 2012). The positive association between maintenance tours and discretionary tours suggests that there are further discretionary activities that are not chained with maintenance activities. Although this requires further research, a possible explanation may be that some maintenance activities are primarily performed during business hours (e.g., bank visits, appointments) whereas many discretionary activities are conducted after business hours. The disconnect between the timing of these activities may result in separate discretionary tours.

We further found that more mandatory tours lead to less online shopping. This finding may suggest that individuals commuting for work trips may prefer in-store shopping over online shopping if they can chain their shopping trips with work trips or shop during their lunch break. However, we did not find any significant relationship between online shopping and maintenance tours nor between online shopping and discretionary tours. In part, this may be due to the aggregation of both shopping travel and non-shopping travel (e.g., personal business, appointment, errands) in the “maintenance tours” variable. Non-shopping activities might not have a direct relationship with online shopping, and as a result, the model did not show a significant relationship.

Mokhtarian et al. (2006) noted that ICT use may have mixed effects on leisure-related travel, as in some cases ICT use can promote new leisure travel whereas in other cases, the adoption of ICT is can reduce leisure travel. These contradictory effects of ICT use on discretionary travel might have caused the statistically insignificant relationships between ICT use (both teleworking and online shopping) and discretionary travel in our model.

Impact of socio-demographics on teleworking, online shopping, and travel behavior

The effects of exogenous variables, notably the socio-demographics of individuals, on the endogenous variables are also of interest. Our results show that having a graduate/post-graduate degree, working full-time, being 18–54 years of age, living in a household with income greater than $100,000 per year, and having fewer children than average are associated with an increased likelihood of teleworking. Gender, vehicle ownership, and being in a single-adult household had no significant impact on teleworking. Online shopping, on the other hand, was performed less by older adults (aged more than 55), and single-adult households shopped online less than households with multiple adults. The latter result may be due to a combination of lower consumption levels in smaller households and policies of online shops that make shopping online for small quantities more expensive, such as minimum order quantities. Being employed (full-time or part-time) and having children present in the household also reduced online shopping behavior.

Regarding travel behavior, not owning a vehicle reduces maintenance and discretionary tours, whereas the number of mandatory tours tends to increase with the number of children in the household. The latter may in part be driven by travel to pick up or drop off children. Being employed full-time or part-time results in more mandatory tours and fewer non-mandatory tours, and overall, male travelers are less likely to make separate maintenance and discretionary tours.

Comparative analysis of tour-based and trip-based models

An in-depth comparative analysis, which is presented in detail in the appendix, Sections A2 and A3, shows that the direct effects between teleworking, online shopping, and the travel outcome variables depend upon the outcome variable used. This observation holds for both the trip-level and tour-level models. While the results for the individual outcome variables may be valid, the diverging findings make it difficult to answer the question, "what is the overall effect of teleworking and online shopping on travel?" This corroborates the need for a holistic view of the impact of ICT use on travel, using multiple indicators as the tour-based latent variable model does (Fig. 2). Overall, comparing the tour-based latent variable model to tour-based single-indicator models, we observe that the former found a similar or greater number of significant effects of ICT use on travel than the single-indicator models, and the direction and magnitudes of the relationships were consistent. This underlines the fact that using multiple travel indicators provides a more holistic view of the impact of ICT use on travel.

A comparison between the trip-level single-indicator models and the tour-level single-indicator models shows that the impacts of ICT use on travel identified by the models depend on whether trip purposes are assigned based on the individual trip purpose or based on the tour that a trip is part of. Some of the effects that were significant in the single-indicator trip-level models were found to be insignificant in the tour-level single-indicator models and vice-versa. This is discussed in further detail in the appendix. The results in Section A2 indicate that a tour-level analysis that accounts for interdependencies within tours can provide insights that are missed by the trip-level analysis. Furthermore, they show that some effects that are detected at the trip level are not of the same relevance at the tour level, possibly because additional trips are added to tours that were going to be made anyway or because reductions in individual trips do not necessarily result in a reduction in tours.

Implications for travel survey design on the ICT–travel relationship

To understand the sensitivity of our results to the length of the travel diary and to support future research on ICT use and travel, this paper also analyzes the impact of survey methods on the model results regarding the relationship between ICT use and travel. The results indicate that one-day activity-travel diaries may not be effective in capturing the effects of ICT use on travel that can be detected with a one-week activity-travel diary. By comparing the estimation results of the various models, we found that the models based on the one-day diaries faced three issues. First, the delivery variables failed to capture the frequency of online shopping and led to poor performance of the measurement models. This is likely because shopping does not occur daily. Moreover, individuals might concentrate their online shopping on certain days, such as weekends, resulting in delivery patterns that are not evenly distributed throughout the week.

Second and relatedly, the one-day diary fails to capture lagged modification effects. For instance, if a person shops online during the week and consequently modifies their shopping travel on the weekend, a one-day travel diary would fail to measure this modification of travel. This issue can be remedied by collecting longer-duration activity-travel diaries, e.g., by extending the tracking period to one week or more. Alternatively, researchers could measure travel patterns before and after individuals increase their ICT use, or ask survey participants to report their past and current ICT use and travel behavior, i.e., conduct a quasi-longitudinal survey (Le et al. 2022; Xi et al. 2020a).

Third, considering the two different approaches to creating one-day diaries, the difference in assigned travel day (i.e., either including weekdays only or both weekdays and weekends) resulted in differences in observed travel patterns, which in turn affected the coefficients of the latent variables in the structural parts of the models. This suggests that one-day travel diaries struggle to capture daily variations in travel and ICT use and therefore may yield biased results. Moreover, one-day travel diaries have a strict cutoff at midnight, such that tours that start in the evening and finish after mid-night are not fully recorded. Similarly, one-day travel diaries also have trouble capturing commute travel by night shift workers, which may cause bias in the data, in particular since there is also an association between night shift work and socio-demographics.

Our results confirm that the length of the activity-travel diary may affect the observed impact of ICT use on travel. Thus, a shorter travel diary duration may be less effective at capturing the actual effects of ICT use on travel.

Strengths and limitations of this study

This study contributes to the literature by innovating upon prior studies that considered telework and online shopping separately and modeled travel at a trip level. We address these shortcomings by accounting for trip chaining and the complexity of travel. First, this study simultaneously captures both teleworking and online shopping behavior and quantifies their impact on travel behavior as well as the relationship between them. Second, modeling travel at the tour level enables us to incorporate tour complexity and trip chaining and thus capture individual activity-travel behavior more realistically than trip-based analyses. Third, we relied on a one-week travel survey, which enables us to capture modification effects on travel that may not occur on the same day on which a person shops online or performs telework. Fourth, this study is among the few studies to analyze how the length of the travel-activity diary affects the detected relationships between teleworking, online shopping, and travel, thereby contributing to the literature on travel survey methods.

This study has several limitations. First, we classified tours based on a primary activity performed during the tour, thereby omitting information about trips for non-primary purposes (i.e., trips for a purpose of lower priority than the primary purpose of the tour) that were embedded in mandatory and maintenance tours. Second, shopping trips were not considered on their own and were grouped with other non-mandatory trips. This may have limited our ability to specifically investigate the relationship between online shopping and shopping travel. Third, the Puget Sound travel-activity diary measured the number of days when individuals received deliveries from online orders, but it did not measure the total number of deliveries during the travel day(s) or week. Doing so could have enabled a more precise measurement of the online shopping behavior latent variable. Moreover, data on package deliveries will represent a lagged effect of online shopping, though the consideration of deliveries and travel over the course of one week reduces the impact of this issue. Fourth, our model did not control for the effect of land use patterns, which may affect teleworking duration and trip chaining behavior. For instance, people living in suburban areas may telework more frequently. Lastly, the model did not account for intra-household interactions or the clustering effect (i.e., correlation between members of the same household), even though the final dataset included individuals who belonged to the same households (Shah et al. 2021).

Conclusions

The purpose of this study was to simultaneously quantify the relationship between teleworking, online shopping, and tour-based travel behavior at an individual level. It accounts for tour-forming by including measures capturing trip chaining and tour complexity and emphasizing the importance of the hierarchy of activities involved in a tour. We found modification effects where teleworking indirectly increases online shopping, reduces mandatory and maintenance tours, but has no significant impact on discretionary tours. Mandatory tours reduce maintenance tours and online shopping, whereas maintenance tours have a positive impact on discretionary tours. We did not find a statistically significant relationship between online shopping and maintenance tours and discretionary tours, nor between teleworking and discretionary tours. In an additional analysis concerning the duration of travel-activity diaries, we found that one-day travel-activity diaries may not provide a full picture of the impact of ICT use. One-day travel diaries also suffer from other shortcomings, such as an inability to capture tours that go past midnight, which may disproportionately exclude specific groups of individuals such as night shift workers.

Our study findings have several implications for transportation practice. First, while past studies focused separately on the effects of online shopping and teleworking, our results show that these two activities may have additional interactions between them. This also suggests that other components of telemobility, such as teleconferencing, telehealth, or e-learning, should not be ignored in future research on the effects of ICT use on travel. Second, our results show that virtual and physical activity and travel are intertwined and should be considered in the same model. The interactions between physical mobility and telemobility may complicate the modeling and forecasting of travel behavior and travel demand, and ignoring them can lead modelers to overlook important effects.

Acquiring a complete picture of the effects of telemobility in all its forms on travel is particularly important due to the ongoing changes to mobility patterns following the COVID-19 pandemic and in light of constant improvements in telemobility technologies and services. Some virtual forms of engagement that were introduced due to constraints during the pandemic may become a permanent part of life in the future. Therefore, there is a need for further studies on the effects of ICT use on travel behavior that consider the many different types and aspects of ICT and travel behavior and that do so simultaneously to capture possible interaction effects. As an example, investigating the impact of the level of teleworking, such as part-time or full-time status, on travel would be an important future research avenue. A further research need is on the topic of telehealth, to understand which types of healthcare visits are being replaced by virtual means and the respective impact on travel behavior.

Lastly, the findings of this paper concerning the duration of travel-activity diaries are of importance to both practitioners and researchers who conduct travel surveys. They show that longer diaries can capture ICT use more accurately and reveal relationships between ICT use and travel that are not visible or adequately captured in one-day diary data. Importantly, travel-activity diary data covering longer time frames may also allow researchers to better understand modification effects of ICT use on travel, as such effects are very difficult to detect without suitable data.

Our study provides several directions for future research. To gain a more detailed picture of tour forming (or trip chaining) behavior, tour complexity, and their interactions with activity scheduling, future research should develop an approach that does not conceal secondary activities behind the primary activities of a tour. More studies are needed to explicitly measure and incorporate maintenance and discretionary trips that are embedded in tours for higher-priority activities, and to better quantify trip chaining behavior and tour complexity. Future studies should also consider household-level models that capture intra-household activity scheduling and travel interactions. This would support the understanding of the effect of various types of telemobility on household travel patterns rather than individual travel patterns. With regard to the interaction between online shopping and in-store shopping, future studies should test the effects of maintenance tours and discretionary tours on online shopping behavior. Likewise, future studies can examine whether mandatory tours influence teleworking.

Appendix: Comparative analysis of tour-based and trip-based models

A1. Methodology

Following the approach described in Sects.Data processing and Model specification and analysis approach, we first aggregated the data at the trip level, with each trip classified based on the activity purpose at its destination. Since a trip-level latent variable model with the structure shown in Fig. 1 failed to converge using the same sample of 545 individuals that underlies the model shown in Sect. Modeling the relationship between ICT and tour complexity, the comparative analysis was performed with path models. Instead of latent variables capturing travel, each path model used one of the three indicators of the travel-related latent variables, i.e., travel time, number of trips, and percent chained VMT. In three of the models (labeled M1-M3 hereafter), the aggregation of the variables was based on the trip purpose, and in a further three models (labeled M4-M6), it was based on the tour purpose. As an example, in Model M1, the three travel-related latent variables were replaced with the respective travel time indicators, as shown in Fig. 3. In Model M1, to determine an individual's travel time for mandatory trips, the total travel time of all trips for mandatory purposes was calculated. Models M2 and M3 used the number of trips and percent of chained VMT instead of the travel times. In Models M4-M6, the purpose assigned to each trip was the primary purpose of the tour that the trip was part of.

A2. Results

Table 6 shows the goodness-of-fit statistics for the single-indicator models M1-M6 as well as the tour-based latent variable model. As can be seen, the tour-based latent variable model has a better fit compared than the six single indicator models, and the CFI values of all six single-indicator models suggest that these models have a comparatively poor fit. The estimation results of Models M1-M6 are shown in Figs. 3, 4, 5, 6, 7 and 8.

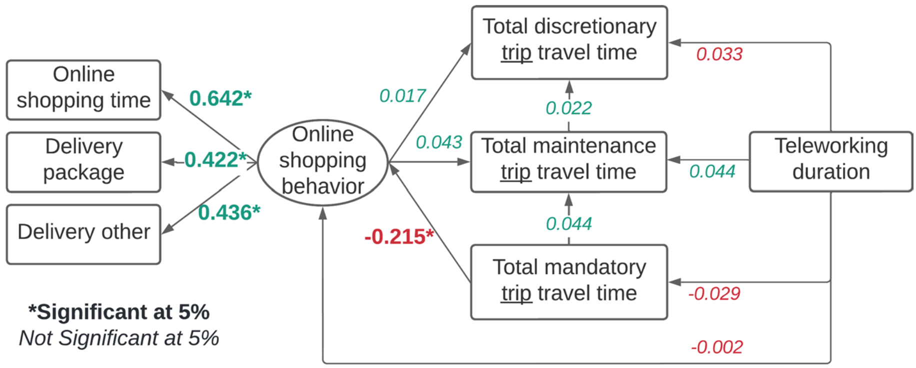

Fig. 3 Trip-level model: Direct effects considering Travel time indicator (M1)

A3. Discussion

A comparison between the tour-based latent variable model and Models M4-M6 shows that the various single-indicator models were only able to identify subsets of the relationships found by the tour-based latent variable model. Additionally, a comparison between the trip-level models (M1-M3) and the tour-level models (M4-M6) shows that the results regarding the impacts of ICT use on travel differ depending on whether trip purposes are assigned individually or based on the tour they are part of. For instance, in the trip-level models, the relationship between teleworking and the number of mandatory trips is significant, whereas the relationship between teleworking and travel time for mandatory trips is insignificant. In the tour-level models, both relationships are significant. Furthermore, models M2 and M3 found that both online shopping and teleworking significantly reduce the number of discretionary trips and the percent of chained VMT for discretionary travel, but the counterparts of these models with the tour-level aggregation did not find this relationship to be significant. Taking Model M2 and M5 as an example, this indicates that while online shopping and teleworking may reduce the number of trips made for discretionary purposes, they do not significantly affect the number of tours for discretionary purposes.

However, given that teleworking does appear to significantly reduce maintenance and mandatory tours in Model M5, the results suggest that discretionary travel that was previously weaved into those tours is not resulting in a significant increase in discretionary tours to compensate. As discretionary activities are the most negotiable, people might just chain them with other non-negotiable activities once the original primary activities are lost in order to avoid separate tours for those discretionary activities. To the extent that new discretionary tours are formed, multiple discretionary trips may be aggregated into a small set of tours that does not correspond to a statistically significant increase. This is an example of the additional types of insights that a tour-level analysis that accounts for interdependencies within tours can provide above and beyond the insights that can be gained by focusing only on the trip level.

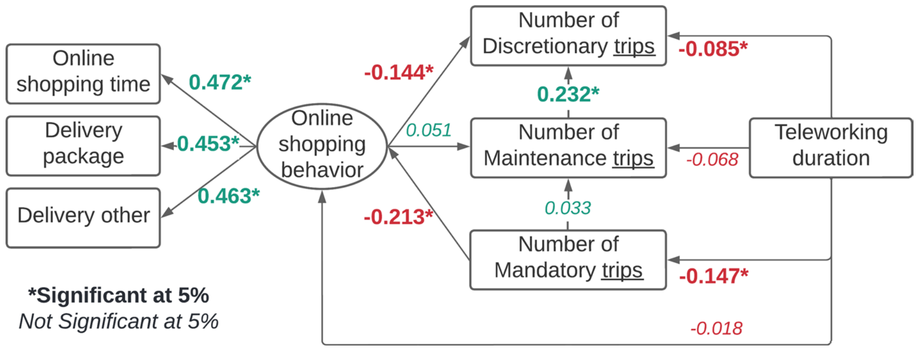

Fig. 4 Trip-level model: Direct effects considering Number of trips indicator (M2)

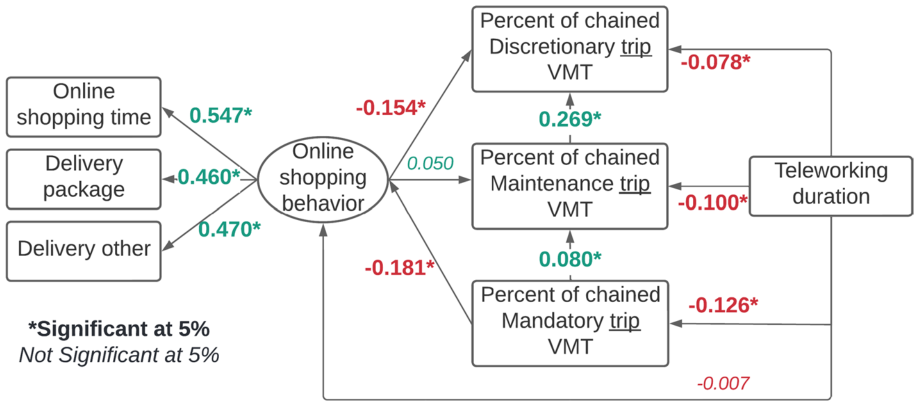

Fig. 5 Trip-level model: Direct effects considering Percent of chained VMT indicator (M3)

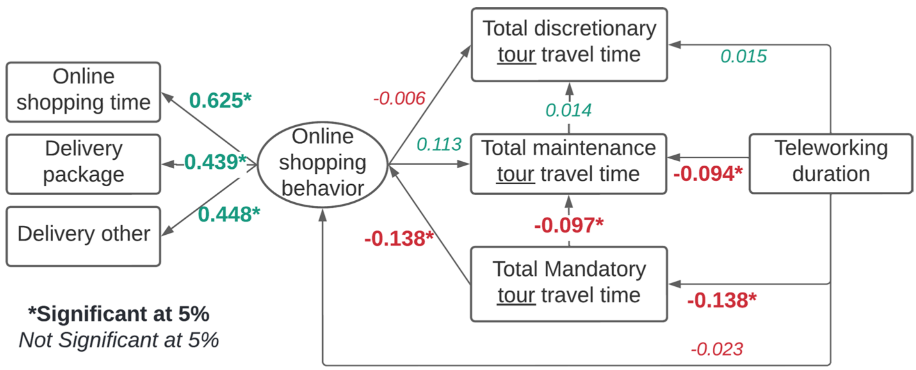

Fig. 6 Tour-level model: Direct effects considering Travel time indicator (M4)

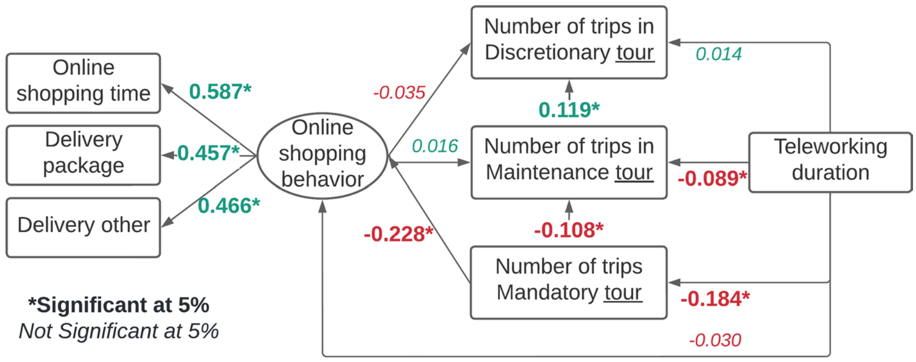

Fig. 7 Tour-level model: Direct effects considering Number of trips indicator (M5)

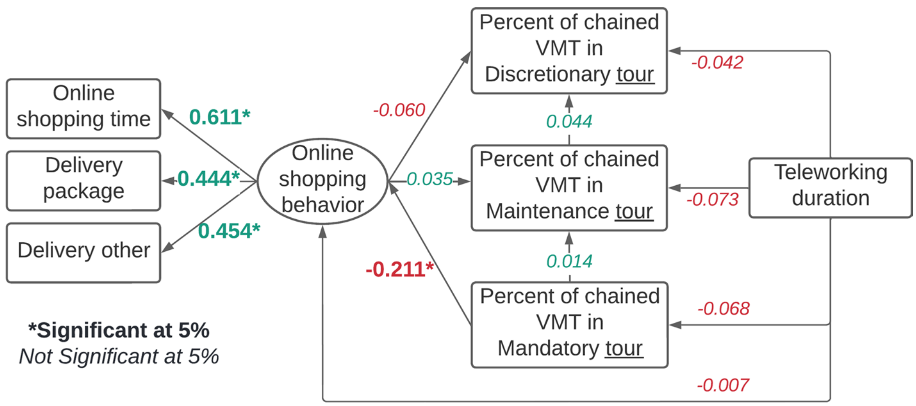

Fig. 8 Tour-level model: Direct effects considering Percent of chained VMT indicator (M6)

Table 6 Comparison of Goodness-of-fit statistics: Simpler path models

Goodness-of-fit statistic		RMSEA	SRMR	CFI
Standard		< 0.05: good fit, < 0.08: fair fit		The greater, the better
Tour-based model (Fig. 2)		0.033	0.044	0.925
Trip-level models	Travel time (M1)	0.042	0.049	0.703
	Number of trips (M2)	0.039	0.049	0.756
	Percent of Chained VMT (M3)	0.039	0.049	0.754
Tour-level models	Travel time (M4)	0.047	0.051	0.670
	Number of trips (M5)	0.036	0.048	0.797
	Percent of Chained VMT (M6)	0.038	0.049	0.725

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Declarations

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

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