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Synergistic and threshold effects of telework and residential location choice on travel time allocation

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ABSTRACT

Much of the literature shows a great interest in debating whether telework has a complementary or substitution effect on people's travel demand. Relatively fewer studies analyze the modification effect of telework on individuals' activity-travel patterns. This study adopts a novel analytical approach to explore the influences of the duration of telework on sustainable travel. The empirical study builds upon a smartphone-based GPS travel survey conducted in the Puget Sound Region of Washington State. The merit of this research is twofold. We first investigate the threshold effects of the duration of telework and built environment characteristics on the shares of travel time spent riding public transit and engaging in active travel. The results can directly inform telework and land use policies. Then, we examine the synergistic effects of the duration of telework and the built environment on both travel outcomes. The findings suggest well-designed telework provisions could complement compact development policies aimed at shifting from automobile dependency to sustainable travel.

1. Introduction

Information and communication technologies (ICTs) are continuously shaping people's daily life and travel behaviors. Many companies in the US are setting up remote work policies to fulfill many employees' desires for flexible working. The share of workers who frequently work at home or other remote locations is increasing every year (Telework Guidance, April, 2011). The three latest nationwide travel surveys suggest that the share of the US employees working at home at least once a week increased from 2.97 % to 6.18 % during 2001–2017 (Federal Highway Administration, 2004, 2011; Federal Highway Administration, 2019). Local governments regard telecommuting as an effective way of alleviating urban traffic congestion and improving travel demand management. On July 25, 2019, the governor of the Greater Boston area proposed the first policy alternative that provides tax incentives to employers who encourage their employees to telecommute (Acitelli, 2019). More recently, the COVID-19 (also known as coronavirus) disruption is demonstrating that telework is a valuable tool for maintaining physical distance that makes communities healthier and more resilient in times of disasters (e.g., Belzunegui-Eraso & Erro-Garcés, 2020). A better understanding of the impacts of telework arrangements on an individual's activity-travel pattern is crucial for planning practices and policy responses.

Cities around the world show a growing interest in utilizing ICT and other related technologies to improve sustainability performance, in terms of economic, social, and environmental dimensions (e.g., Ahvenniemi, Huovila, Pinto-Seppä, & Airaksinen, 2017; Akande, Cabral, Gomes, & Casteleyn, 2019). Teleworking, e-shopping, virtual meetings, and other forms of online activities have the potential to speed up this movement by lowering energy use and greenhouse gas (GHG) emissions (e.g., Kramers, Höjer, Lövehagen, & Wangel, 2014). Earlier research has shown that telecommuting policy is useful to reduce peak-hour traffic congestion and vehicle emissions (Shabanpour, Golshani, Tayarani, Auld, & Mohammadian, 2018; Choo, Mokhtarian, & Salomon, 2005; Pendyala, Goulias, & Kitamura, 1991). Nevertheless, a considerable number of recent studies argue that telecommuting programs should be implemented with caution, giving the counteracting effect on the overall travel demand (e.g., Kim, 2017; Tal, 2008; Zhu, 2012).

Frequent telecommuters usually live far from the workplaces, driving longer distances on commute days as compared to non-telecommuters (Zhu, 2013). They may also drive long distances to the preferred locations for teleworking, such as coffee shops and libraries. For these teleworkers, the saved commuting costs (i.e., time and money) allow them to participate in leisure activities more often (Lachapelle,

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Tanguay, & Neumark-Gaudet, 2018). Besides, other members of the household can drive unused household vehicles to different activities. The overall impacts of telework arrangements on travel demand \depend on how individuals and households allocate the saved costs from commuting trips. In other words, telework arrangements modify travel patterns at both individual- and household-level.

Saxena and Mokhtarian (1997) suggest that an individual tends to have a larger number of trip-ends around home on telecommuting days. The spatial context at a residential location has a stronger effect on teleworkers' activity-travel patterns than that of non-teleworkers. Although the relationships between the built environment and commuting behaviors have been well documented (Ewing & Cervero, 2010; Handy, Boarnet, Ewing, & Killingsworth., 2002; Stevens, 2017), little is known on how the time spent working online may change the relationships between the built environment and travel behaviors. Many telecommuting programs and land use policies aim to reduce auto dependency and associated negative consequences. We expect that there exists a synergistic effect of the built environment and telework arrangements on promoting sustainable travel.

Encouraging the use of public transport, walking and biking is a tangible solution to a series of social, economic, and environmental problems caused by over-reliance on driving (e.g., Banister, 2008; Gudmundsson, Hall, Marsden, & Zietsman, 2016; Litman, 2019). In this study, we treat the proportions of time spent riding public transit and engaging in active travel among the total amount of time spent traveling as sustainable travel outcomes. This study contributes to the literature by revealing the margins of the average time spent teleworking per day on an individual's travel time spent riding public transit and engaging in active travel. We further explore how such effects vary across different spatial contexts. A gradient boosting decision trees (GBDT) method is adopted to analyze the travel diary data from the 2017 Puget Sound Regional Travel Survey (PSRTS). The research findings offer nuanced guidance to the advocates of telework programs and sustainable mobility. Moreover, the COVID-19 pandemic would change people's habits and out-of-home activity participation behavior to a certain level. Some employees may become more productive when working from home than working at the office, and thus tend to telework longer hours when the quarantine is lifted. Due to the above-mentioned reasons, we believe this investigation will be of interest to both the scientific community and policy makers in the post COVID-19 era.

2. Literature review

According to the classical time geography theory, an individual's activity-travel pattern can be constrained to the spatial and temporal restrictions related to mandatory activities, as well as the travel budget constraints (Chapin, 1974; Hägerstrand, 1970). The workplace locations and schedules are the major anchor points of an employee's activity-travel pattern. Teleworking helps workers remove such spatial and temporal constraints. As an alternative work arrangement, teleworking provides the freedom of managing daily activity patterns based on individual needs. Workers will have higher job-related positive affective well-being if they adopt teleworking as compared to working in the office (Anderson, Kaplan, & Vega, 2015). Telework is also found to have beneficial effects on improving work-life balance and reducing work-family conflict (Gajendran & Harrison, 2007).

The initial goal of creating telecommuting programs is to reduce travel demand and ease peak-hour traffic congestion (Nilles, 1994). Earlier research findings supported advocating telecommuting programs can lead to substantial transport-related benefits (Hamer, Kroes, & Van Ooststroom, 1991; Pendyala et al., 1991; Salomon, 1998). Later, the possibly complementary effects of telecommuting had been gradually recognized (Mokhtarian, Handy, & Salomon, 1995; Mokhtarian, 1998). More recent studies cautioned multilevel stakeholders that the transport-related benefits of telecommuting mentioned among earlier studies can be overestimated (Kim, Choo, & Mokhtarian, 2015; Kim, 2017; Tal, 2008; Zhu, 2012, 2013; Zhu, Wang, Jiang, & Zhou, 2018).

Using data from the 2001 and 2009 US National Household Travel Survey, Zhu and his colleagues conducted a series of empirical studies to identify the impacts of telecommuting on individuals' travel patterns. Zhu (2012) investigated the influences of telecommuting on workers' one-way commute trips, and daily work and non-work trips. He found that telecommuting increases total travel distance (for both commuting and non-commuting trips), and therefore inferred telecommuting and personal travel are indeed complements. In line with this, Zhu (2013) extended his research by studying the effects of telecommuting status of one worker on his or her partner. The results show that, at the household level, the presence of a regularly telecommuting employee increases both commute distance and duration significantly. However, this study did not find any significant relationships among household members regarding their telecommuting choice, and regular commute distance and duration. Zhu et al. (2018) examined the heterogeneous effects of telecommuting across different MSA (Metropolitan Statistical Areas) sizes. The results reveal that telecommuting policies have positive influences on both commute distance and duration, regardless of the size of MSAs. These studies plot a big picture illustrating the positive relationship between telecommuting and the overall vehicle travel demand. Previous studies using data from the pilot programs have limitations related to the narrow scope and sample selection bias, but they still provide sound information based on the specific research scopes.

The connections between telecommuting and transportation can generate from four paths (Melo & Silva, 2017; Mokhtarian, 1990; Salomon, 1986): 1) *substitution* if the usage of telecommuting results in a reduced need for travel ; 2) *complementary* if the use of telecommuting eventually increases travel demand; 3) *modification* if the use of telecommuting changes an employee's activity-travel pattern, such as transport mode choices and departure times, and 4) *neutrality* if there is no impact on actual travel demand. As discussed above, the debate on whether telecommuting exposes a complementary or substitution effect has been extensively revisited. Relatively fewer studies focus on the modification effect of telework on an individual's daily activity-travel pattern.

Asgari, Jin, and Du (2016), and Asgari and Jin (2017) conducted structural analyses for the relationships between time allocated among non-mandatory activities, different telecommuting patterns, and the decisions to commute. The studies constructed research datasets based on the 2010–2011 Regional Household Travel Survey in the New York metropolitan region. Asgari et al. (2016) found that full-day telecommuters spend more time on discretionary activities. On the contrary, part-day telecommuters engage in maintenance and out-of-home shopping errands for a longer duration. Lachapelle et al. (2018) and Chakrabarti (2018) responded to the question on whether telecommuting has a positive effect on sustainable travel outcomes. After analyzing the 2005 Canadian General Social Survey, Lachapelle et al. (2018) found that different types of telework arrangements have different impacts on increasing active travel and reducing traffic congestion. As compared to working in the office, working from home only is found to be associated with less overall travel time by an average of 13 min. Chakrabarti (2018) analyzed the 2009 NHTS data and found that telecommuting frequency can significantly promote active travel and physical activity. Individuals who telecommute more than four times per month are more likely to make at least one transit trip per month compared to non-telecommuters. For telecommuters, there exists a significant reduction in driving on telework days. However, the annual driving distance for telecommuters is usually longer than that for non-telecommuters (Chakrabarti, 2018). Research findings in North America support that, if implemented appropriately, telecommuting programs can positively influence the process of moving away from automobile dependency to sustainable alternatives.

Teleworkers are likely to generate new travel if the conventional needs could be satisfied at home. The net effect is a modification of existing travel patterns at both individual-level and system-wide

Fig. 1. Study Region – Four Counties of Puget Sound Region.

(Salomon, 1985). In light of all above, there is an imperative to carry out a detailed analysis of the amount of time spent teleworking on transport outcomes. This study contributes twofold to the literature by taking the advantages of the recently popularized machine learning algorithms. First, it provides useful information regarding the degree to which the duration of telework will influence an individual's travel time spent on sustainable transport modes. Revealing the thresholds also reflects how an employee will allocate total travel time to other travel modes, particularly to automobiles, when his or her daily time spent teleworking changes. Second, this study presents the synergistic effects of the spatial context and the duration of telework on travel time allocation. The impact of telecommuting policy may differ when the amount of time spent teleworking falls into different ranges. The thresholds identified in this study offer crucial information for planners and decision-makers who are interested in promoting the effectiveness of telework provisions.

3. Research design

3.1. Data and variables

This study develops the research dataset using the 2017 Puget Sound Regional Travel Survey (PSRTS). The survey collected household- and personal-level activity and travel pattern information from the Puget Sound Regional Council (PSRC)'s four-county region, namely, King, Pierce, Snohomish, and Kitsap counties (see Fig. 1). The survey recorded participants' information about mode choices, time spent on travels, trip purposes, and some other trip features on multiple days. Puget Sound region is considered as an attractive area for young and tech-friendly people, as well as a relatively more transit-friendly built environment than other US metropolitan areas (Puget Sound Regional Council, 2019). The focus of this research is to analyze the effects of the duration of telework on sustainable travel, and how such effects vary across different spatial contexts.

Apparently, the time spent online influences a person's daily activity-travel time use pattern. Some participants responded to the survey for multiple days. We then calculated the daily averages for two variables that represent a person's time spent on virtual mobility: the duration of telework and time spent for online shopping. For this study, the duration of telework is the key interest variable. Time spent for online shopping is one of the most important control variables as it is another crucial component of virtual mobility and has been found to influence an individual's time allocation significantly (Asgari & Jin, 2017; Asgari et al., 2016; Kramers et al., 2014). A dominant share of previous literature focuses on telework and online shopping among all types of ICT activities while analyzing ICTs' impacts on travel behavior (Dong, Cirillo, & Diana, 2018). Controlling for online shopping provides us with the opportunity to measure the true effect of telework on activity-travel time use patterns.

The proportions of time spent riding public transit and engaging in active travel among the total amount of time spent traveling during the survey period are separately calculated to measure two major forms of sustainable travel. Table 1 summarizes the details of the above factors and other individual-level characteristics for our final sample. Those survey participants were excluded from the final sample if they had incomplete information on our variables of interest. The total number of valid participants is 3233. Individuals who do not have recorded times spent by different transport modes (i.e., auto, public transit, and active travel) were also removed from our analysis as they cannot be used for exploring relative travel time.

We measure the built environment at each participant's place of residence following the classical transportation planning literature (Ewing & Cervero, 2010). We link the survey data with the Environmental Protection Agency (EPA)'s Smart Location Database (SLD)[1] using geocoded household locations. A Census Block Group (CBG) is selected as the spatial unit, which presents a reasonable scale to understand the neighborhood level spatial effects on near home activities. Table 2 presents the percentile distribution of continuous variables used in this study, namely, time spent online, built environment characteristics, and

[1] Link: https://www.epa.gov/smartgrowth/smart-location-mapping#SLD

Table 1
Variable definition and sample statistics.

Variables	Variable Description	Value set	Mean (±S.D.) / Percentage
Travel time spent on sustainable travel			
The share of riding public transit	The proportions of time spent riding public transit among the total amount of time spent traveling during the survey period	Continuous variable: **R**+	0.19 (±0.33)
The share of engaging in active travel	The proportions of time spent engaging in active travel among the total amount of time spent traveling during the survey period	Continuous variable: **R**+	0.19 (±0.30)
Time spent online (in minutes)			
Duration of telework	The average amount of time spent on teleworking on the survey days	Continuous variable: **R**+	60.28. (±132.31)
Duration of online shopping	The average amount of time spent on online shopping on the survey days	Continuous variable: **R**+	10.02 (±20.28)
Built environment at the places of residences (census block group level)			
Population density	Persons×1000/sq. mi.	Continuous variable: **R**+	12.31 (±11.28)
Job density	Jobs×1000/sq. mi.	Continuous variable: **R**+	12.19 (±44.18)
Land use mixture	Entropy variable using the 8-tier employment categories from Census Longitudinal Employer-Household Dynamics (LEHD) 2010	Continuous variable: **R**+	0.58 (±0.26)
Pedestrian-oriented intersections	Pedestrian-oriented intersections/sq. mi.	Continuous variable: **R**+	153.92 (±100.36)
Frequency of peak-hours transit services	Aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period	Continuous variable: **R**+	161.25 (±196.73)
Vehicle ownership and household income			
Household income		Categorical variable	
Less than 25k	= 1 if household income >=$0 and <=$24,999; = 0 otherwise		6.12 %
25k to 50k	= 1 if household income >=$25,000 and <=$49,999; = 0 otherwise		12.53 %
50k to 75k	= 1 if household income >=$50,000 and <=$74,999; = 0 otherwise		15.96 %
75k to 100k	= 1 if household income >=$75,000 and <=$99,999; = 0 otherwise		15.09 %
100k to 150k	= 1 if household income >=$100,000 and <=$149,999; = 0 otherwise		25.15 %
150k+	= 1 if household income >=$150,000; = 0 otherwise		25.15 %
Household vehicles per person	Number of household vehicles/Household size	Continuous variable: **R**+	0.71 (±0.44)
Other demographics			
Age		Categorical variable	
Young Adults (Age 18–34)	= if age > = 18 and < = 34; = 0 otherwise		45.38 %
Mid-Aged Adults (Age 35–54)	= if age > = 35 and < = 54; = 0 otherwise		39.62 %
Older Adults (Age 55–74)	= if age > = 55; = 0 otherwise		15.00 %
Gender		Categorical variable	
Female	= 1 if female; = 0 if male		47.32 %
Male	= 1 if male; = 0 if female		52.68 %
Driver's license		Categorical variable	
Licensed driver	= 1 if licensed driver; = 0 if non-driver		95.08 %
Non-driver	= 1 if non-driver; = 0 if licensed driver		4.92 %
Educational Attainment		Categorical variable	
Less than Bachelor	= 1 if highest grade completed is at most associates degree; = 0 otherwise		21.00 %
Bachelor	= 1 if highest grade completed is bachelor's degree; = 0 otherwise		44.70 %
Graduate	= 1 if highest grade completed is at least a graduate degree; = 0 otherwise		34.30 %
Race and ethnicity		Categorical variable	
White	= 1 if race White; = 0 otherwise		70.49 %
Hispanic	= 1 if race Hispanic; = 0 otherwise		4.21 %
Non-Hispanic others	= 1 if race Non-Hispanic others; = 0 otherwise		25.30 %
Number of children		Categorical variable	
No child	= 1 if no child; = 0 otherwise		78.87 %
One child	= 1 if one child; = 0 otherwise		11.91 %
Two or more children	= 1 if number of children > = 2; = 0 otherwise		9.22 %
Employment types		Categorical variable	
Full time	= 1 if full time; = 0 otherwise		80.92 %
Part time	= 1 if part time; = 0 otherwise		10.86 %
Self-employed	= 1 if self-employed; = 0 otherwise		8.23 %
Working Hours		Categorical variable	
Less than 20	= 1 if number of hours typically worked per week < = 20; = 0 otherwise		7.89 %
20 to 40	= 1 if number of hours typically worked per week >20 and < = 40; = 0 otherwise		44.11 %
More than 40	= 1 if number of hours typically worked per week > 40; = 0 otherwise		48.00 %

Note: sample size = 3233.

Table 2
Percentile distribution of continuous variables.

Variable	Minimum	50th Percentile	75th Percentile	90th Percentile	95th Percentile	Maximum
The share of travel time spent riding public transit	0	0	0.26	0.84	1	1
The share of travel time spent engaging in active travel	0	0	0.29	0.71	1	1
Duration of telework	0	0	41	240	390	840
Duration of online shopping	0	0	15	30	45	270
Population density	26.93	9333.49	15281.06	24957.29	33163.95	110780.90
Job density	0.10	3719.52	9607.55	24113.73	49914.66	739316.10
Land use mixture	0	0.65	0.76	0.84	0.93	0.94
Pedestrian-oriented intersections	0.45	131.61	212.96	283.35	332.58	908.94
Frequency of peak-hour transit services	0	119	207	307	444	1839.33

Table 3
Pearson correlations between the key variables and travel time spent on sustainable transport alternatives.

	The shares of travel time spent	
	Public Transit	Active Travel
Duration of telework	−0.070**	0.107**
Duration of online shopping	−0.017	0.022
Population density	0.170**	0.217**
Job density	0.040**	0.128**
Land use mixture	0.059**	0.102**
Pedestrian-oriented intersections	0.165**	0.219**
Frequency of peak-hour transit services	0.102**	0.227**

Note: **Significant at the 95 % level.

Table 4
Relative contributions of independent variables on travel time spent patterns.

Categories	Variable	Public Transit		Active Travel	
		Rank	Rel. Imp. (%)	Rank	Rel. Imp. (%)
Average daily time spent online	Duration of telework	7	6.20	6	7.83
	Duration of online shopping	11	2.51	11	3.32
Built environment attributes	Population density	4	8.84	3	12.29
	Job density	2	9.17	4	11.13
	Land use mixture	6	7.08	7	7.30
	Pedestrian-oriented intersections	5	7.98	5	8.18
	Frequency of peak-hour transit services	3	9.12	1	14.82
Incomes and Vehicle ownership	Household income	9	2.95	9	4.17
	Household vehicles per person	1	28.47	2	14.67
	Driver's license ownership	8	3.28		
Demographics	Number of hours worked per week	14	2.27	10	4.17
	Employment types	13	2.42		
	Education background	15	2.04	8	4.36
	Race and ethnicity	10	2.74	12	2.79
	Number of children	12	2.47		

Note: This study considers a relative influence of 2% to be non-trivial. The rank and relative importance of those variables with a relative contribution smaller than 2% are not presented in the table (Dong et al., 2019).

travel outcomes.

The bivariate relationships between our variables of interest are presented in Table 3. The duration of telework is statistically significant and positively associated with the share of travel time spent engaging in active travel. However, this factor is a negative predictor of the share of travel time spent riding public transit. All built environment features are significantly associated with two sustainable travel outcomes and follow the expected signs. The scales of the estimated coefficients suggest that the effects of spatial context around the residences tend to have a stronger influence on travel time spent on active travel compared to public transportation. For multivariate analysis, we first estimate linear regression models for riding public transit and engaging in active travel separately (as shown in Appendix A). Indeed, the pre-defined linearity assumption can lead to the estimates of multivariate analyses become severely biased. First, an explanatory variable can be an effective predictor of one outcome variable within a certain range; however, it may not influence the outcome variable significantly when it does not fall within such a range. Second, both the relationships shown in Table 3 and regression-based estimates neglect the existence of multiple confounding effects among explanatory variables (Ding, Cao, & Næss, 2018). We follow with a novel machine learning approach.

3.2. Modeling approach

This study adopts a gradient boosting decision trees (GBDT) model to explore the threshold effects of the duration of telework on the shares of travel time spent in sustainable travel alternatives. In recent years, the GBDT model has been widely used in transportation research. It provides more precise prediction and reliable identification of the relative influence of each independent variable than traditional regression models (Chung, 2013; Ding, Cao, Næss et al., 2018; Ding, Cao, & Wang, 2018; Dong, Cao, Wu, & Dong, 2019; Ma, Ding, Luan, Wang, & Wang, 2017; Tao, Wang, & Cao, 2020; Zhang & Haghani, 2015). The nature of this approach is that it reaches the results based on a combination of many single decision trees. This approach captures the interactions among predictors automatically. Thus, the GBDT model outperforms the traditional regression models on relaxing the multicollinearity issue and addressing the interaction effects between these predictors.

Some studies have offered the details of understanding the GBDT algorithm from an intuitive way (e.g., Ding, Cao, Wang et al., 2018; Dong et al., 2019; Tao et al., 2020). Gradient boosting combines M decision trees to generate a model with better predictive performance than utilizing a single decision tree. Given a sample of (y, x), the goal of GBDT algorithm is to minimize the following loss function:

$$L(y, F(x)) = (y - F(x))^2 \tag{1}$$

The output in Step m ($0 < m \le M$) is (Friedman, 2001):

$$F_m(x) = F_{m-1}(x) + \xi \times \sum_{j=1}^{J} \gamma_{jm} I(x \in R_{jm}), \quad where 0 \le \xi \le 1 \tag{2}$$

where ξ is the learning rate, and J is the number of regions partitioned by a decision tree. γ_{jm} is the value of optimal gradient for the region R_{jm} that makes the current function $F_m(x)$ obtain the smallest loss. $I = 1$ if $x \in R_{jm}$ and $I = 0$ otherwise. For a single decision tree T, a measurement to approximate the relative contribution of an explanatory variable x_κ in predicting the response is:

$$I_\kappa^2(T) = \sum_{t=1}^{J-1} \hat{\tau}_t^2 I(v(t)) = \kappa) \tag{3}$$

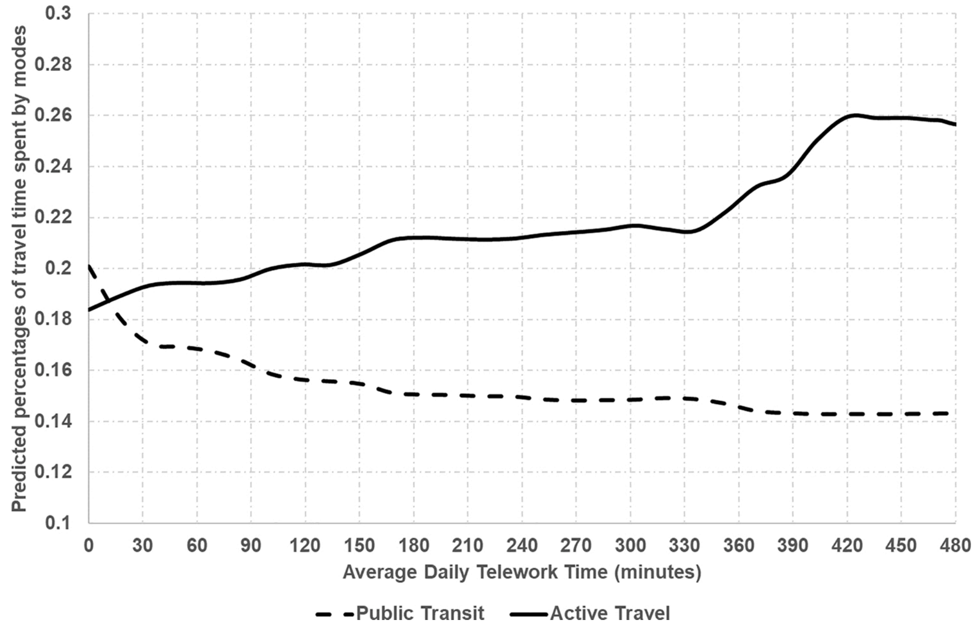


Fig. 2. The marginal effects of the duration of telework.

where $\hat{\tau}_t^2$ is the improvement in squared error term when an explanatory variable x_κ is the splitting variable that refers to *v(t)* in the Eq. (3). For a group of decision trees, the relative contribution of a specific explanatory variable is obtained by averaging the information from all trees. The GBDT algorithm estimate the marginal effects of this explanatory variable following the same logic (Friedman, 2001; Hastie, Tibshirani, & Friedman, 2009).

This study builds the GBDT model using the "gbm" package in R. The marginal effects (i.e., partial dependence) at different points are computed in "pdp" package. Two GBDT models are developed for the shares of travel time spent riding public transit and engaging in active travel. For each model, the predictors include all the variables listed in Table 4. Three crucial parameters need to be predetermined. We fix the shrinkage or learning rate as 0.001 to make a balance between predictive variance and computing time (Chung, 2013; Ding, Cao, Næss et al., 2018, 2018b; Dong et al., 2019). Tree complexity is another vital model parameter that reflects the actual interactions between explanatory variables (Friedman, 2001). Determining this information requires a data-driven analytical process. We set a maximum of 10,000 trees and adopt a five-fold cross validation method to alleviate overfitting (Ding, Cao, Næss et al., 2018, 2018b; Dong et al., 2019; Tao et al., 2020). This study estimates a sequence of models by increasing the interaction depths from one to twenty. We compare the performance of these models based on Root Mean Square Error (RMSE). In general, for both public transit and active travel models, RMSE does not decrease substantially after the value of tree complexity reaches 15. We therefore choose the final models built on the tree complexity of 15. The values of RMSE for public transit and active travel models are 0.304 and 0.277, respectively. The models are generated with 2339 and 3017 decision trees. The pseudo-R^2 values, "the fraction of variation explained by model" (Schonlau, 2005), are 0.493 and 0.540 for public transit and active travel models, respectively (the R^2 of the linear regression models with the same set of independent variables are 0.144 and 0.152).

4. Analytical results

4.1. Relative contributions of independent variables

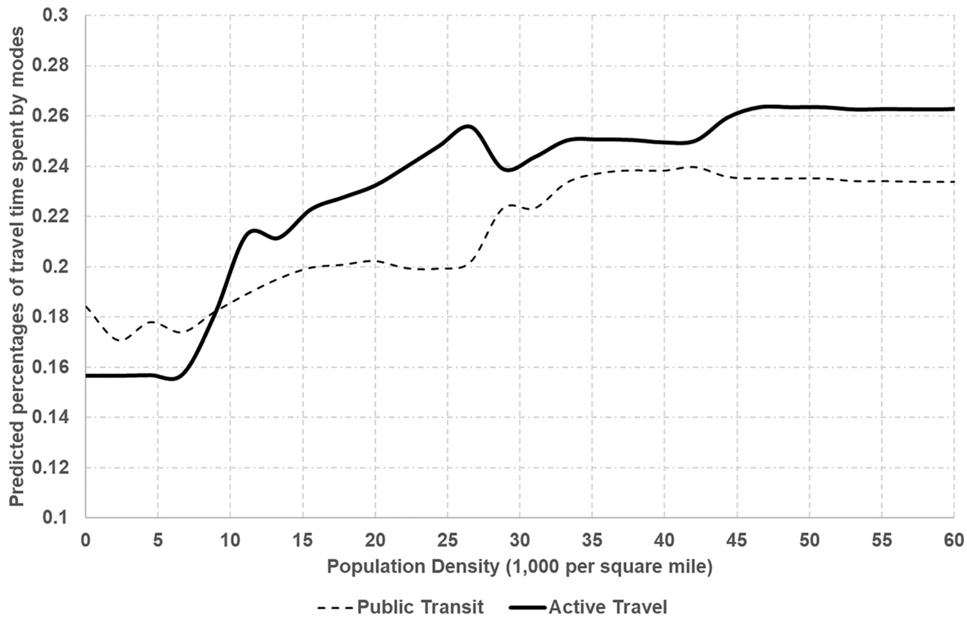
Table 4 summarizes the relative contributions of independent variables in predicting travel time allocated to two forms of sustainable transport outcomes. Not surprisingly, the duration of telework is a significant predictor of both the shares of travel time spent riding public transit and engaging in active travel. The relative contributions of this factor are 6.2 % and 7.8 %, respectively. These relative contributions show that the effect of teleworking on travel time spent on sustainable travel is much larger than that of online shopping. Our descriptive statistics suggest that, an individual's average time spent teleworking is about six times as much as that of online shopping. Thus, duration of telework exacts a stronger modification effect on people's daily activities. The findings regarding the impacts of teleworking on sustainable travel respond to the previous evidence that travel time savings due to teleworking can influence both transit rides and active travel (Chakrabarti, 2018).

The built environment is another important category of our variables of interest. Built environment characteristics are found to contribute to about 42.2 % and 53.7 % of the shares of travel time spent riding public transit and engaging in active travel, respectively. The results reveal residential location choice could play a crucial role in influencing time spent traveling (Ewing & Cervero, 2010; Stevens, 2017). The household income level and vehicle ownership also have strong effects on time spent on sustainable travel. Significant effects of both income levels and vehicle ownership on sustainable travel are parallel with the previous studies (Chakrabarti, 2018; Mckenzie, 2014; Shin, 2019). Our results further reveal that other demographics collectively have a much smaller contribution in predicting transport outcomes as compared to those factors representing the neighborhood environment and personal wealth. The finding is consistent with Ding, Cao, Wang et al. (2018).

4.2. Non-linear effects of the duration of telework and built environment variables

We then investigate how the amount of time spent teleworking and built environment characteristics affect daily travel time allocation. We draw the figures to show the changing relationships across the entire range of values between our variables of interests and two outcome variables. The COVID-19 outbreak will accelerate the telework trend, possibly for the long term. The margins in Figs. 2–5 can provide nuanced guidance on transport demand management and formulating effective land use policies under various circumstances.

Some nationwide analyses report that increasing the frequency of



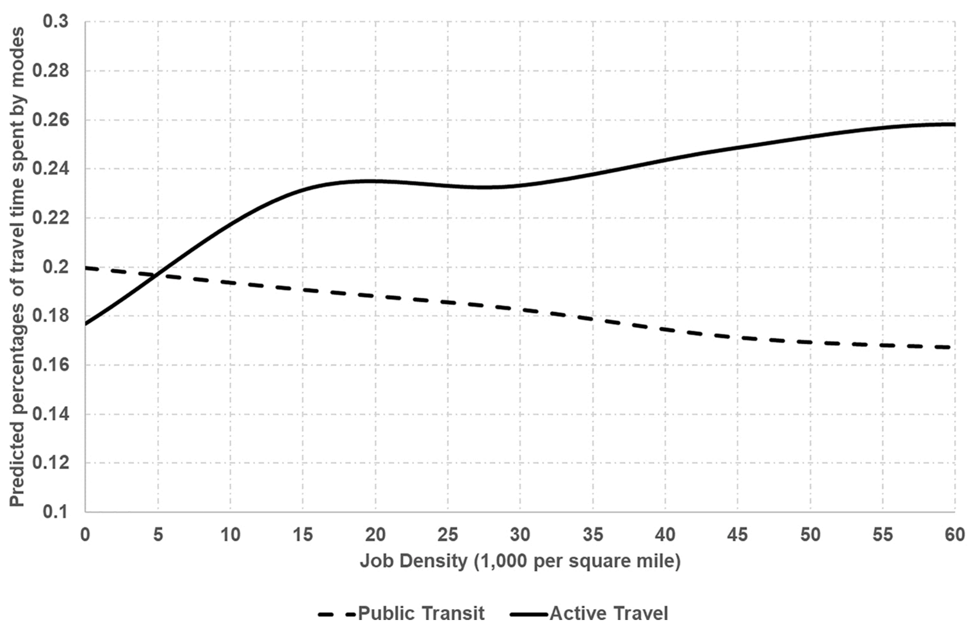
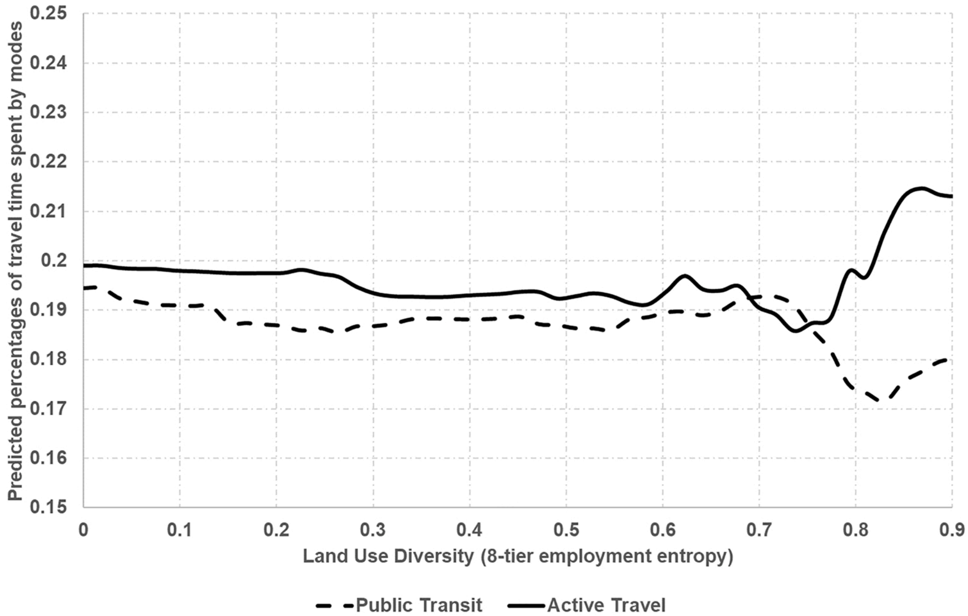


Fig. 3. The marginal effects of density variables.

telecommuting may induce vehicle travel demand at the individual level (e.g., Zhu, 2012; Zhu et al., 2018). This study finds that duration of telework has an overall negative association with travel time allocated to riding public transit. As shown in Fig. 2, when the average daily time spent teleworking increased from 0–30 min, the share of travel time spent riding public transit decreased from 0.2 to 0.17. Beyond this range, the change in the proportion of time spent riding public transit among the total travel time is relatively smaller. The results imply that more time spent teleworking would not necessarily exert much influence on a person's decision to ride public transit. As to travel time spent in active travel, Fig. 2 shows that duration of telework exposes a positive effect when it increases from 0–420 min. The share of travel time spent in active travel gradually grows from 0.18 to 0.26. For the total share of travel time spent by public transit and active modes, the value varies between 0.35 and 0.45 as the changes in duration of telework. The data used in this study shows that, if many employees continue to work remotely and put in longer hours in the post COVID-19 era, their travel time allocated to sustainable travel modes will not change substantially due to this issue.

As expected, population density has an overall positive relationship with the shares of travel time spent riding public transit and engaging in active travel (as shown in Fig. 3). The effective range is between 5000 and 30,000 people per square mile. Beyond this range, the relationships tend to be stable. We further find that the difference in the shares of total travel time spent in active travel could reach around 0.1 between residents living in low-density neighborhoods and those in high-density neighborhoods. Consistent with the bivariate statistics, as population density increases, engagement in active travel has a larger magnitude of the increment than that of riding public transit. Employment density has a small, negative, and almost linear relationship with travel time spent riding public transit (as shown in Fig. 3). The difference in the shares of travel time spent riding public transit reaches about 0.03 between



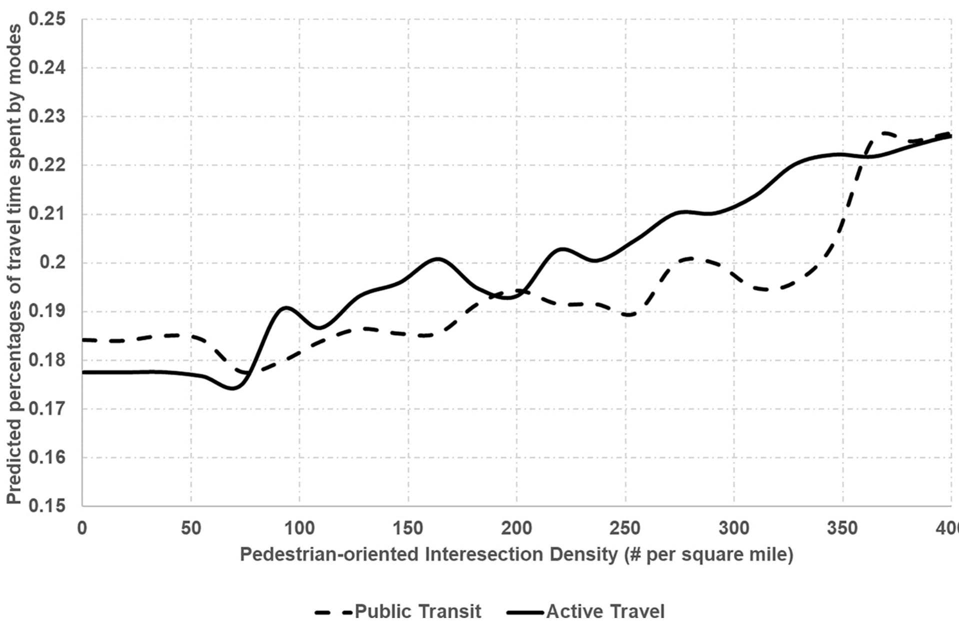


Fig. 4. The marginal effects of other land use variables.

people living in a neighborhood with very high employment density and those residing in communities with very low employment density. For the share of travel time spent engaging in active travel, we observe that within the range between 0 and 20,000 jobs per square mile, increasing job density has a positive effect on engagement in active travel. Fig. 4 illustrates that, compared to the density variables, the margins of land use entropy index to travel outcomes are more erratic and less effective. The growth of the number of pedestrian-oriented intersections tend to increase the shares of travel time spent riding public transit and engaging in active travel (as shown in Fig. 4). Specifically, the difference in the shares of travel time spent engaging in active travel reaches approximately 0.05 between individuals who reside in neighborhoods with pedestrian-oriented street design and those living in communities with more auto-oriented street network. A similar relationship is observed for the share of travel time spent riding public transit.

Somewhat surprisingly, as shown in Fig. 5, this study finds that the frequency of transit service during the evening peak period has a stronger effect on the share of travel time spent engaging in active travel than that of riding public transit. If an individual moves from a place with very low levels of peak-hour transit service frequency to a neighborhood with high levels of peak-hour transit service frequency, the share of his or her travel time spent engaging in active travel can increase by more than 0.1. This value is about 0.04 for travel time spent riding public transit. The larger influence of public transit supply on the relative travel time spent in active travel may be due to the fact that completing access/egress trips between transit stops and home/activity destinations involves non-motorized trips (i.e., bicycling, walking, etc.). Future studies are encouraged to explore the underlying reasons for the observed differences.

4.3. Synergistic effects between the built environment and the duration of telework

As explained above, the effects of built environment characteristics

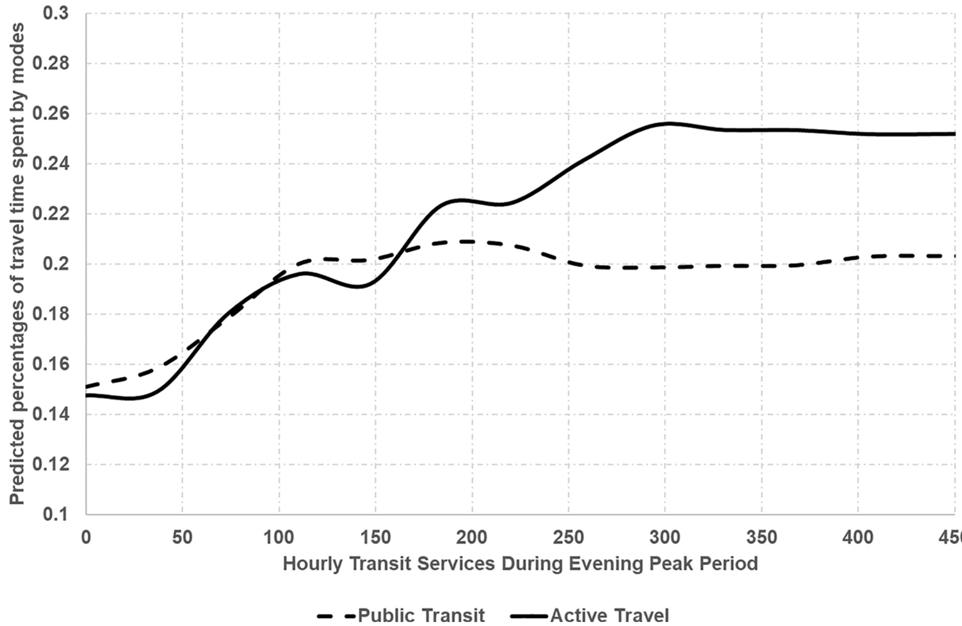


Fig. 5. The marginal effects of peak-hour public transit services.

around the residences and the duration of telework are not simple, and most of them do not seem to correlate with the shares of travel time spent riding public transit and engaging in active travel linearly. Planning practices should be cautious about the thresholds related to local contexts. Another goal of this study is to explore the spatially varying effects of the duration of telework on travel time use patterns. Figs. 6 and 7 present the changing trends of these effects, instead of predicting the exact numbers.

Generally, if an individual spends more time on teleworking, he or she will allocate less time to riding public transit, regardless of the choice of residential location (as shown in Fig. 6). The result is somewhat interesting given the fact that the built environment around the residences collectively carries about 42 % on the variation of the share of travel time spent riding public transit. The duration of telework contributes to about 6%, which is much less than the contribution of each built environment attribute. It can be inferred that the duration of telework has a more obvious effect on the share of travel time spent riding public transit than built environment factors. We speculate that this might be because the existence of multiple confounding effects from other factors representing incomes and vehicle ownership, and sociodemographics. In addition, the data analyzed in this study does not provide information regarding residential location preferences. These attitudinal factors may largely explain both the predictive power of the built environment and travel outcomes. In turn, implementing telework and compact development programs together would not be a straightforward path to encourage more public transit rides.

As shown in Fig. 7, the built environment around the residences has a more visible effect on changing the relationship between the duration of telework and the share of travel time spent engaging in active travel. People who spend more time on teleworking and live in neighborhoods with higher residential and employment densities, well-connected street networks, and sufficient public transit supplies are found to use active transport modes more than the others. Also, it is worth noting that promoting land use diversity does not modify the relationship between the duration of telework and the share of travel time spent engaging in active travel as much as the changes in other built environment characteristics.

5. Discussion and conclusions

Using the 2017 Puget Sound Regional Travel Survey data, this study examined the joint effects of the average time per day spent teleworking and built environment characteristics on sustainable travel outcomes, controlling for duration for online shopping, income levels, vehicle ownership, and other demographics. A gradient boosting decision tree (GBDT) was applied to predict the shares of travel time spent riding public transit and engaging in active travel. To the best of our knowledge, this is the first study that investigates the effects of the duration of telework on the links between the built environment and travel behavior. This is also one of the few studies that analyze the modification effect of the duration of telework on an individual's daily activity-travel pattern. The research findings provide insights into the integration of telework arrangements and land use policies.

Previous studies have shown great interests in discussing telecommuting choice and frequency have either substitute or complementary effects on total travel demand (e.g., Hamer et al., 1991; Pendyala et al., 1991; Salomon, 1998; Mokhtarian et al., 1995; Mokhtarian, 1998; Kim et al., 2015; Kim, 2017; Tal, 2008; Zhu, 2012, 2013; Zhu et al., 2018). This study measures telecommuting as the average amount of time spent on teleworking on the survey days. The results demonstrate that the net effect of telework on sustainable travel is modification. We argue that remote work policies may be beneficial in promoting the use of sustainable travel modes, such as walking, biking, and public transit, and thereby reduce automobile dependence. At this point, it is important to underline that the association between telework and sustainable travel is not linear as shown in our study. Our research identifies the thresholds of teleworking duration in which there is a meaningful association. These thresholds can help to guide policy provisions and practices about the promotion of sustainable travel. Even if these thresholds provide some guidelines to local authorities, the results may be different in other contexts. Future policy making need to scrutinize the proper range of teleworking durations in their localities prior to implementing any associated policies, strategies, and plans. If these policies are not well developed, they may possibly induce the amount of vehicle travel. The possible modification effect of teleworking on sustainable travel should not be presumed as either positive or negative.

This study confirms a general positive relationship between the amount of time spent teleworking and the share of travel time spent

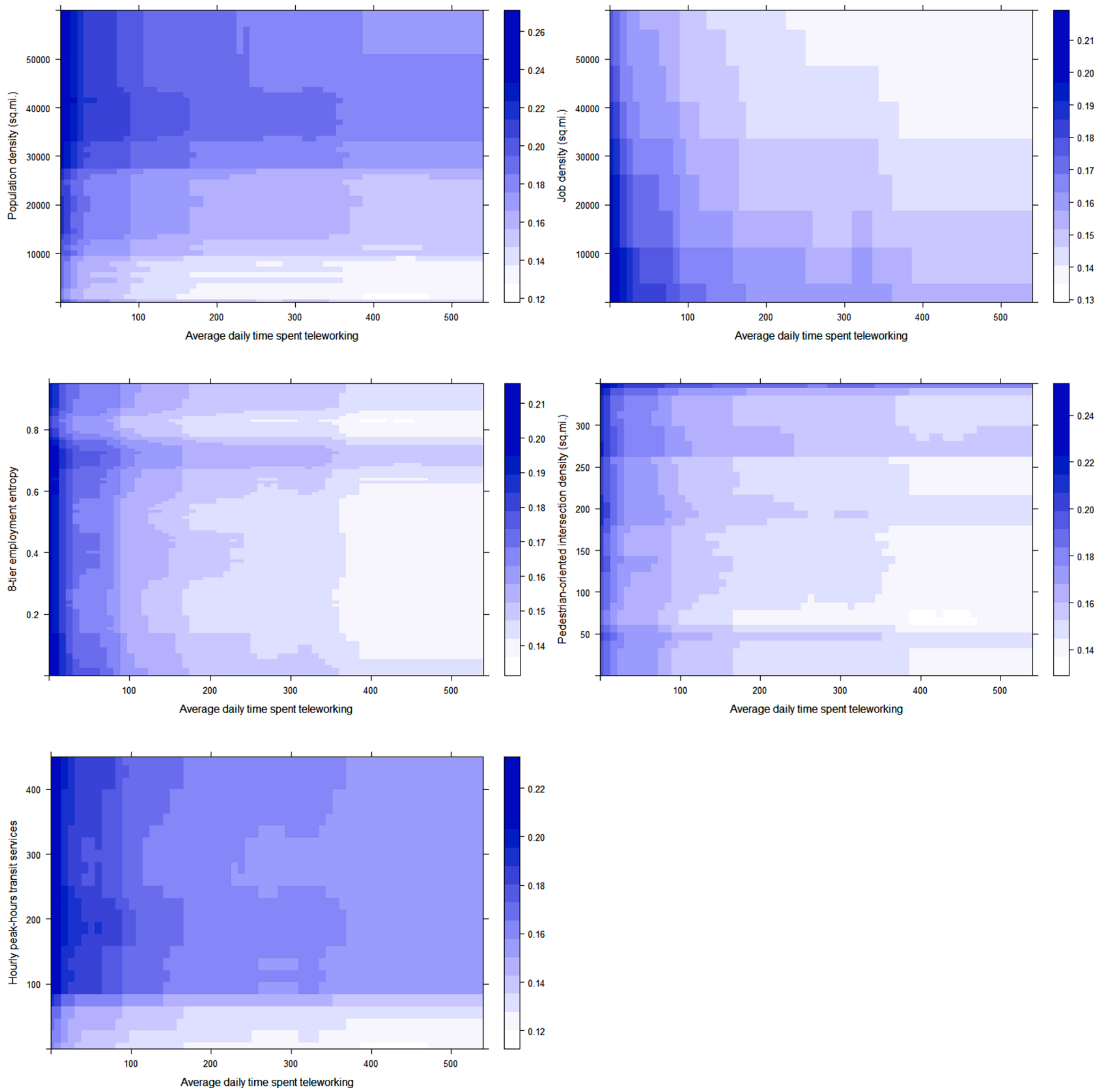


Fig. 6. Synergistic effects of the duration of telework and built environment factors on the share of travel time spent riding public transit.

engaging in active travel. This highlights that people tend to allocate part of their saved commute time to walking or bicycling, which benefit physical and mental health (De Nazelle et al., 2011). New investments in pedestrian, bicycling, exercise, and other recreational facilities can complement telework programs. When the average time per day spent teleworking is within 30 min, travel time spent riding public transit decreases as long as the duration of telework increases in an almost linear way. Overall, the duration of telework shows salient non-linear effects on travel time spent riding public transit. We argue that teleworking alone is not an adequate policy tool to encourage more transit trips. People who study the impacts of teleworking on sustainable travel can utilize our findings, particularly those regarding active travel engagement.

Regarding the effects of the built environment, the contributions of this study are twofold. Prior studies have found that the built environment plays a crucial role in predicting both driving distance and commute mode choice (Ding, Cao, Næss et al., 2018, 2018b). This study offers new evidence on the link between travel time usage and the built environment at the place of residence. Specifically, our model estimates suggest that the built environment explains 42 % and 54 % of travel time spent riding public transit and engaging in active travel, respectively. The difference shows that daily physical activity is more sensitive to the changes in the built environment characteristics around the residences as compared to riding public transit. The relatively larger effect of built environment on active travel than public transit is consistent with the previous studies (Chakrabarti, 2018; Shin, 2019). Admittedly, built environment characteristics affecting active travel are different than those affecting transit use (Ewing & Cervero, 2010). Since the latter group includes variables that are household level rather than CBG level, such as proximity of places of residences to transit stops, and the number of stations per unit area. These variables are not available in our dataset, and they can explain the relatively weaker association between the built environment and public transit rides that were found in this study.

Furthermore, the verified synergistic effects between the built environment and the duration of telework on the shares of travel time spent engaging in active travel offer insightful implications to planners and decision-makers. Beyond reducing peak-hour traffic congestion and vehicle emissions, our results imply that telework programs complement compact development policies aimed at shifting from automobile dependency to sustainable travel. A possible explanation is that teleworkers have a higher predisposition towards walking and bicycling, and they tend to engage in physical activities near home more often.

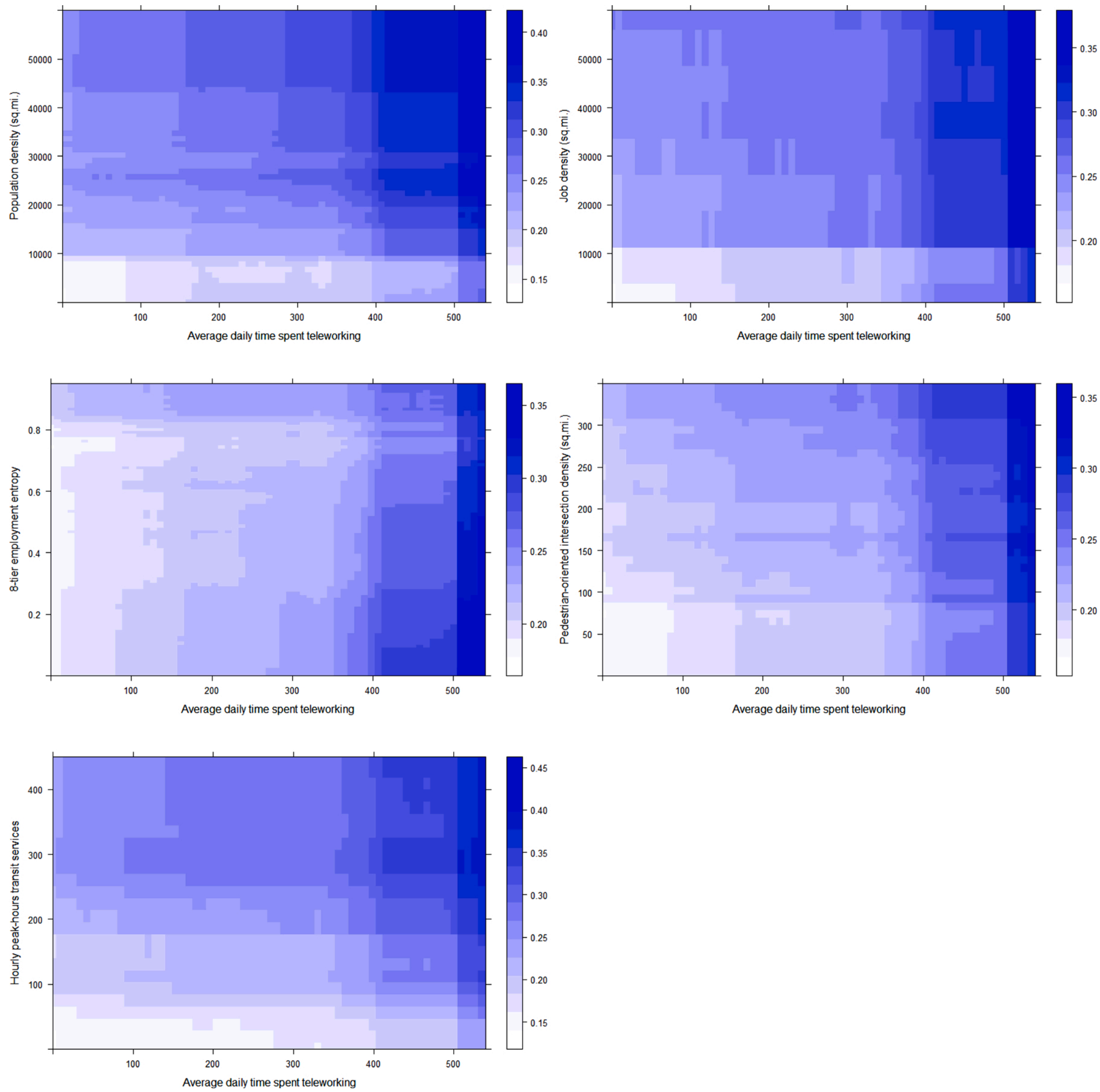


Fig. 7. Synergistic effects of the duration of telework and built environment factors on the share of travel time spent engaging in active travel.

Implementing appropriate telework arrangements should be adopted as a promising practice among transportation planners and professionals if they are pursuing a long-term cultural shift regarding vehicle ownership and usage.

Many people are supposed to travel less after the COVID-19 pandemic is over. They are very likely to avoid public transport and shared mobility services and engage in active travel more frequently (recreationally or in case of short distances) (e.g., De Vos, 2020). It is crucial to know that exploring pathways to support active travel can potentially benefit physical health and enhances subjective well-being. In this study, the estimated threshold effects of built environment characteristics, at least, offer nuanced guidance to local authorities on specific short-term planning efforts.

This study finds that residential location choice can be a powerful predictor of an individual's travel time spent on sustainable travel. However, individuals may choose residential locations based on the predisposition towards specific modes or activities. People who place a high value on walking and bicycling are more likely to choose to live in compact development neighborhoods. This is referred to as residential self-selection in the literature (Cao, Mokhtarian, & Handy, 2009). We acknowledge the preexisting attitudes and preferences can largely influence an individual's decision to travel. Without controlling for the self-selection bias, we cannot predict the true effects of the built environment and the related synergistic effects accurately. Overall, the findings of this study provide concrete evidence to the advocates of sustainable mobility, indicating that telework programs can complement those land-use policies designed for reducing automobile dependency and encouraging active travel.

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Declaration of Competing Interest

The authors report no declarations of interest.

Appendix A

Table A1 presents the results of multiple linear regressions. Based on the size of standardized coefficients, it is feasible to rank the relative

Table A1
Linear regression models.

Categories	Variable	Public Transit Beta	Public Transit p-value	Active Travel Beta	Active Travel p-value
Average daily time spent online	Duration of telework	−0.062	0.000	0.036	0.038
	Duration of online shopping	0.001	0.952	−0.023	0.184
Built environment attributes	Population density	0.009	0.642	0.080	0.000
	Job density	0.022	0.334	−0.019	0.394
	Land use mixture	0.007	0.682	−0.018	0.308
	Pedestrian-oriented intersections	0.042	0.039	0.045	0.023
	Frequency of peak-hour transit services within 0.25 miles of CBG boundary	−0.043	0.078	0.085	0.000
Incomes and Vehicle ownership	Household income (base case: less than 25k)				
	25k to 50k	−0.006	0.839	0.014	0.627
	50k to 75k	−0.029	0.348	−0.008	0.802
	75k to 100k	−0.049	0.118	−0.021	0.487
	100k to 150k	−0.010	0.787	−0.069	0.051
	150k+	−0.064	0.084	−0.048	0.191
	Household vehicles per person	−0.124	0.000	−0.120	0.000
Demographics	Male (base case: Female)	0.033	0.066	0.039	0.024
	Age (base case: Young adults who age 18–34)				
	Mid-aged adults who age 35–54	0.014	0.493	0.021	0.286
	Older Adults who age 55 to 74	0.047	0.017	−0.019	0.326
	Number of hours worked per week	0.031	0.177	0.003	0.909
	Employment types (base case: Full time)				
	Part time	−0.036	0.103	0.006	0.769
	Self-employed	−0.033	0.090	0.029	0.129
	Education background (base case: Less than Bachelor)				
	Bachelor	0.072	0.003	0.076	0.001
	Graduate	0.058	0.017	0.116	0.000
	Race and ethnicity (base case: White)				
	Hispanic	−0.038	0.340	0.008	0.842
	Non-Hispanic others	0.000	0.987	−0.012	0.586
	Number of children (base case: No child)				
	One child	−0.046	0.013	−0.046	0.012
	Two or more children	−0.053	0.006	−0.051	0.009
	Driver's license (base case: non-owners)	−0.073	0.000	0.001	0.968
R-squared		0.045		0.079	
Adjust R-squared		0.036		0.071	
Number of observations	3233				

importance of all the independent variables. However, the pre-defined linearity assumption can lead to the estimates of multiple linear regressions become severely biased. Multicollinearity may be a concern for the regression models. Moreover, the relationship between an independent variable and the dependent variable may be varying along the entire range of the independent variable. Estimating a multiple regression model is meaningful since it be regarded as complements to the tree-based ensemble approach by offering some statistical inferences.

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