Income moderates the nonlinear influence of built environment attributes on travel-related carbon emissions

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Abstract

Policymakers have adopted built environment policies to modify people's travel behavior and the related emissions. However, most studies have not examined the interactive impact between income level and built environment attributes on travel-related carbon emissions (TCE), and only several studies consider their nonlinear relationships. With data from the Twin Cities, US, this study estimated the nonlinear effects of built environment attributes and demographics on TCE. It further examined the interactive impacts between household income and built environment attributes. The findings highlight that demographics exert a greater influence on TCE than the built environment. Employment status, job accessibility, and gender are the most important predictors. Besides individual nonlinear relationships, household income and built environment attributes have salient interactive impacts on TCE. The results suggest that providing environment friendly and affordable transportation choices to low-income population, switching to clean energy vehicles, and offering more matched job opportunities to low-income population near their residence are promising to create a sustainable transportation system.

1 Introduction

Greenhouse gas (GHG) generated from transportation accounts for a large share of the total GHG emissions. In the US, the transportation sector produces approximately 27% of the GHG emissions in 2020 (EPA, 2022). Therefore, it is important to discourage people's dependence on auto use to reduce GHG emissions and their influence on the environment. A considerable number of scholars in the field of urban planning are extensively researching the impact of policies related to the built environment on shaping people's travel behavior and the consequent GHG emissions (Cao & Yang, 2017; Choi & Zhang, 2017; Wu et al., 2019).

However, there are two research gaps in the existing literature. First, most studies only focus on the entire population when studying the built environment effects on travel-related emissions but fall short of examining the heterogenous effects across the subpopulations with different income levels in the region. As people from different income groups differ in their travel behavior and respond differently to the built environment policies, results of the whole population might not be applicable to those low-income and/or high-income groups. This creates equity concerns. Second, the nonlinear relationships between the built environment and travel-related emissions have not received sufficient attention from scholars and practitioners yet. More studies considering nonlinear relationships are still needed to supplement the understanding of the complex relationships between built environment attributes and travel-related emissions.

To address these research gaps, this study applies a machine learning approach called Extreme Gradient Boost to estimate the contributions of built environment attributes and demographic variables on people's daily travel-related carbon emissions (TCE) and the related nonlinear relationships with the data from the Twin Cities area in US. In addition, this study examines the interactive effects between household income and built environment attributes on TCE. Specifically, this study plans to answer two research questions:

1) How do built environment attributes and demographics influence TCE when considering nonlinear relationships?

2) What are the interactive impacts between household income and built environment attributes on TCE?

This study has two important contributions to the existing literature. First, this study examines the individual nonlinear impact of built environment and demographics on travel-related carbon emissions. The results supplement the limited literature on this topic. Second, this study explores the interactive impacts between household income and built environment attributes on travel-related carbon emissions. The results provide great insights into the policies to create a sustainable and equitable transportation system.

The rest of this paper is organized as follows. Section 2 reviews the literature on the impact of built environment attributes on travel-related emissions. The data and methodologies used in this study are introduced in Section 3. Section 4 presents and discusses the results. The conclusions and policy implications are provided in the last section.

2 Literature review

Travel-related emissions consist of emissions from multiple travel modes such as cars and transit and determined by the share, distance, and emission rate of each travel mode. Studies focusing on the built environment and travel-related emissions have shown that density, land use mix, street network design, transit supply, and distance to city center are important built environment attributes correlated with travel-related emissions. Specifically, their results show that density (Cao & Yang, 2017; Choi & Zhang, 2017), land use mix (Choi & Zhang, 2017; Wang et al., 2013), and street network connectivity (Wang et al., 2013; Xu et al., 2018) are all negatively correlated with travel-related emissions. On the contrary, distance to city center (Cao & Yang, 2017; Wang et al., 2017) and distance to transit stop (Barla et al., 2011; Boarnet et al., 2017) have positive relationships with travel-related emissions.

The literature, however, has seldom examined the heterogeneous built environment effects on travel-related emissions for people with different income levels. Many studies have shown that people from different income groups behave differently in their travel behavior. According to the 2017 National Household Travel Survey, households with incomes over 100,000 dollars on average have over 4,000 trips every year. For households with incomes less than 15,000 dollars, the number of annual person trips drops to approximately 1,500 (FHWA, 2018). In addition, the low-income population responds differently to the built environment policies compared with the higher-income population. This is because low-income people have limited choices in their travel modes and work opportunities. For example, with the travel data from the Twin Cities, USA, Tao and Cao (2021) found that people living in high-income areas only reduce their vehicle usage when transit supply increases to a certain threshold. However, people living in low-income areas keep reducing their driving amount when transit supply increases and do not have a threshold. As travel-related emissions are closely related to people's travel behavior, the effects of built environment attributes on travel-related emissions are expected to be different for people with various income levels and, thus, need more studies.

Moreover, there is a growing consensus among scholars that the associations between attributes of the built environment and travel behavior should be defined as nonlinear relationships (Boarnet, 2017; Van Wee & Handy, 2016). Nonlinear relationships indicate the incremental impact of a single built environment variable on travel behavior does not remain static, but rather, it varies based on the specific value of that built environment variable. Numerous empirical investigations have substantiated the existence of nonlinear relationships between the built environment and travel behavior (Ding et al., 2018; Sabouri et al., 2020; Tao et al., 2023; Yang et al., 2021). For example, Ding et al. (2018) found that distance to city center is nonlinearly associated with weekly driving distance in Oslo, Norway. The relationship showed that distance to city center has a moderately positive effect on weekly driving distance when it changes from 0 to 12 km, but this effect increases dramatically when distance to city center exceeds 12 km. Hence, it is plausible to anticipate that the relationships between attributes of the built environment and travel-related emissions may exhibit a nonlinear pattern. Only a limited number of studies have explored the nonlinear relationships between the built environment and travel-related emissions (Gao et al., 2022; Shao et al., 2023; Wu et al., 2019; Yang & Zhou, 2020) and none of them have examined the interactive impact between built environment attributes and demographics. More studies are still needed to examine the generalizability of the results of existing studies.

3 Data and methods

3.1 Data

One of the important datasets applied in this study is the Travel Behavior Inventory (TBI) survey in Twin Cities (Figure 1), in the US (Metropolitan Council, 2019). The Metropolitan Council, which is the local metropolitan planning organization, carried out the TBI survey from October 2018 to September 2019. The survey mainly collected information about people's demographic attributes and travel diaries. To increase the participation of the survey, TBI provided three approaches for people to take part in the survey, including smartphone application, online survey, and call center. All people used the same questionnaire no matter how they participated in the survey. The survey was also available in multiple languages, including English, Spanish, Karen, Oromo, Somali and Hmong. Totally, there were 13,215 people from 6,558 households participated in the survey, providing rich information about the travel behavior in the Twin Cities area. Individuals residing in Minnesota become eligible to apply for a driving license at the age of 16 or beyond. Consequently, this study incorporated participants who were at least 16 years of age. This study included 11,005 participants in the final analysis.

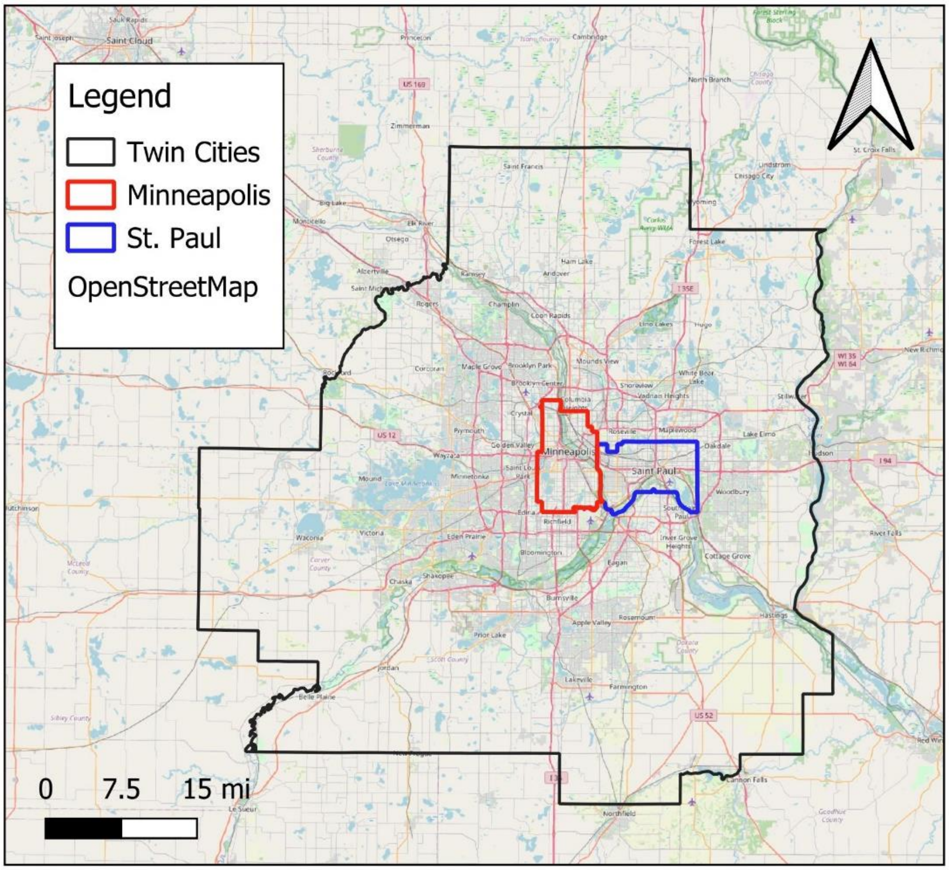

Figure 1. Study area

As to the built environment variables, this study followed Ewing and Cervero (2010) and included five types of variables, including density, diversity, design, distance to transit (e.g., transit supply), and destination accessibility. Since the survey data only provided the residential locations at the census block group (CBG) level, the built environment variables were computed at CBG level accordingly. All the independent variables considered in this study are listed in Table 1.

Table 1. Variable description, data sources, and descriptive statistics (N=11,005)

Variable	Description	Data sources	Mean	Standard deviation
Daily average carbon emission	Personal daily average carbon dioxide emission in pound on weekdays	This study	15.33	19.9
Built environment variables (measured at the census block group (CBG) where the participant live)				
Job accessibility	Number of jobs in thousand that can be reached by auto in 20 minutes	Accessibility observatory[1]	509,862	313,292
Land use mix	The entropy index of land use mix	MGC[2]	0.57	0.21
Intersection density	Number of four- or more-way intersections per square mile		42.31	45.76
Transit stop density	Number of transit stops per square mile as of Sep. 2018	Metro Transit	27.07	34.28
Population density	Number of people per acre	ACS[3]	8.33	10.11
Distance to St. Paul	The driving distance in miles from the centroid of the CBG to downtown Saint Paul	Google map[4]	16.88	9.29
Distance to Minneapolis	The driving distance in miles from the centroid of the CBG to downtown Minneapolis		14.22	8.86
Demographic variables				
Driving license	A dummy variable indicating whether the respondent has a driving license	TBI survey	0.94	0.24
Worker	A dummy variable indicating whether the respondent is employed (full-time, part-time, self-employed)		0.67	0.47
Male	A dummy variable indicating whether the respondent is male		0.45	0.5
Household income	The respondent's household income 1 = Under $15,000 2 = $15,000-$24,999 3 = $25,000-$34,999 4 = $35,000-$49,999 5 = $50,000-$74,999 6 = $75,000-$99,999 7 = $100,000-$149,999 8 = $150,000-$199,999 9 = $200,000-$249,999 10 = $250,000 or more		5.94	2.06
Education level	Educational background of the respondent 1 = Less than high school 2 = High school graduate/General educational development 3 = Some college 4 = Vocational/technical training		5.22	1.79

[1] Accessibility observatory at the University of Minnesota: https://access.umn.edu/
[2] Minnesota geospatial commons: https://gisdata.mn.gov/
[3] American community survey 2014-2018 5-year estimates: https://www.census.gov/programs-surveys/acs/news/data-releases.html
[4] Google maps platform (distance matrix API): https://developers.google.com/maps/documentation/distance-matrix/overview

Variable	Description	Data sources	Mean	Standard deviation
	5 = Associate degree 6 = Bachelor's degree 7 = Graduate/post-graduate degree			
Disability	A dummy variable indicating whether the respondent has a disability		0.04	0.21
Age	Age category of the respondent 3 = 16-17 4 = 18-24 5 = 25-34 6 = 35-44 7 = 45-54 8 = 55-64 9 = 65-74 10 = 75 or older		7.04	1.79
White	A dummy variable indicating whether the respondent is Caucasian		0.86	0.34
Student	A dummy variable indicating whether the respondent is a student		0.08	0.27

3.2 Methods

The dependent variable considered in this study is personal daily average carbon dioxide emissions on weekdays. For simplicity, this study used travel-related carbon emissions (TCE) in the rest of the paper when necessary. With the travel diary information from the TBI survey, this study used Equation (1) to calculate TCE.

$$C = \frac{\sum_1^I \sum_1^{J_i} D_{ij}^k R_k}{J N_{ij}} \quad (1)$$

In Equation (1), j ($j = 1,2,\dots,J$) indicates the jth trip of a day. i ($i = 1,2,\dots,I$) indicates the ith travel day of a participant. k ($k = 1,2,\dots,K$) indicates the kth travel mode of a trip. The travel modes considered in this study include driving, bus transit, light rail transit, and active travel (e.g., walking and biking).

C indicates TCE. D_{ij}^k presents the distance of trip j on day i with travel mode k. R_k is the carbon dioxide emission rate for travel mode k. FTA (2010) provided carbon dioxide emission rates for different travel modes calculated with the data from 2008. Given the facts that power plants have reduced their use of coal to generate electricity and private vehicles have increased significantly in fuel efficiency (i.e., mile traveled per gallon), the carbon emission rates from 2008 were outdated when this study was conducted. Therefore, this study updated the carbon emission rates with the data in 2019 through the methodology provided by FTA (2010). The carbon emission rates used in this study are listed in Table 2. Note that carbon emission rates might be different for different makers and types of vehicles. However, this study did not consider these factors as the trip information provided by TBI survey did not provide the information of the vehicles used in the auto trips. Note that this study did not consider the carbon emission rate for electric private vehicles as the share of electric vehicles in 2019 was very low in Minnesota. According to the US Department of Energy (DOE, 2018), there were only 7,700 electric vehicles registered by 2018, which accounted for approximately 0.1% of all auto registrations in Minnesota.

Table 2. Carbon dioxide emission rates for different travel modes

Travel mode	Carbon dioxide emission rate (pounds per passenger mile)
Driving (Single occupied vehicle)	0.88
Bus	0.64
Light rail	0.43
Active travel	0

N_{ij} is the number of travelers of trip j on day i, which is available in the TBI survey. For some auto trips, multiple people shared the same vehicle. This study assumed the people in the same trip equally shared the associated carbon dioxide emission. This assumption improved the accuracy of the calculation of personal carbon emission compared with several previous studies (Shao et al., 2023; Wu et al., 2019).

Figure 2 presents the distribution of the daily TCE across the Twin Cities. A clear pattern is that people living farther away from the urban area are associated with larger amounts of carbon emissions.

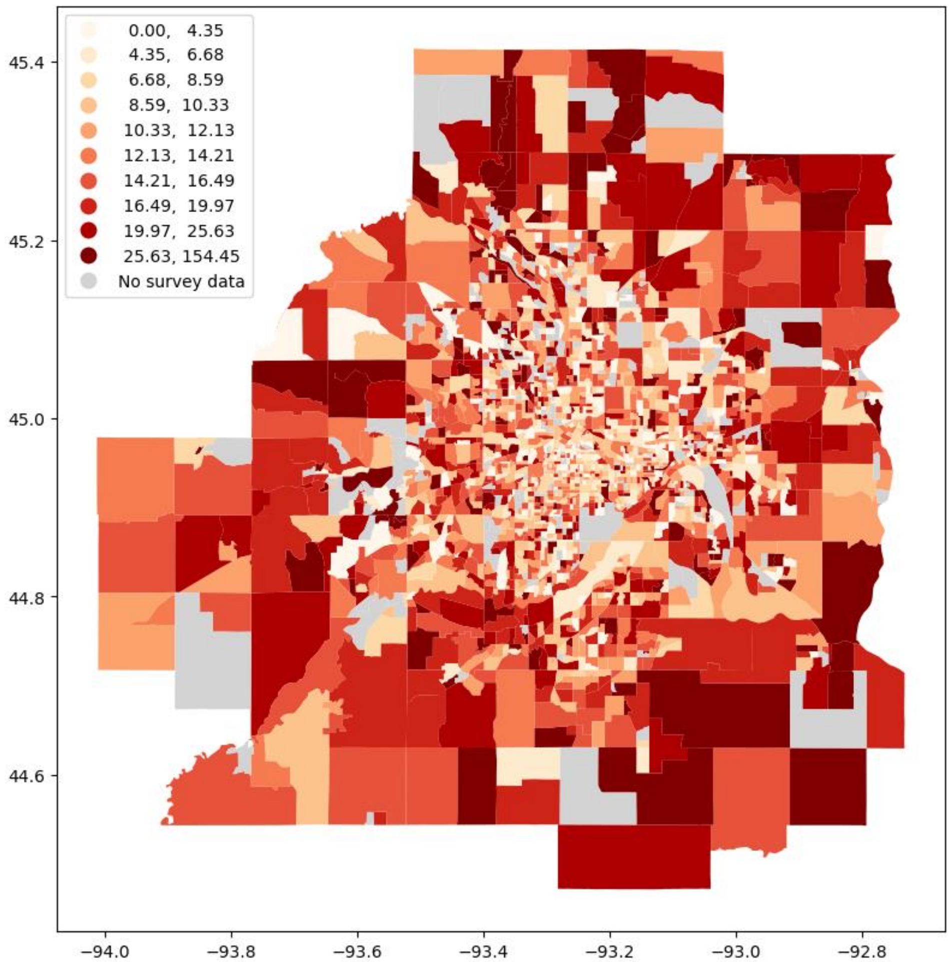

Figure 2. Distribution of TCE in the Twin Cities

This study applied the Extreme Gradient Boost (XGBoost) approach to estimate the nonlinear relationships between travel-related carbon emission and two types of independent variables, i.e., built environment attributes and demographics. XGBoost (Chen & Guestrin, 2016) applies the parallel tree boosting method to significantly to increase the accuracy and speed when fitting the sample. In general, XGBoost applies the decision tree method to split the sample into several subsamples according to certain criteria and combines multiple decision trees into a large complex model.

XGBoost has several advantages compared to traditional statistical models such as linear and generalized linear models. First, XGBoost has no assumptions about the form of the relationships between the dependent and independent variables and, thus, is effective in estimating irregular nonlinear relationships. Second, XGBoost has a better prediction capability.

Third, XGBoost can better handle outliers and missing values. With that said, this study can include more observations in the model, and this could further increase the estimation performance. In addition, compared with other tree-based approaches such as gradient boosting decision trees and random forest, XGBoost is faster in fitting the data as it uses more regulations (Chen & Guestrin, 2016).

This study applied the five-fold cross validation approach to search for the best combination of parameters, including number of decision trees, tree depth, and learning rate. Number of decision trees indicates the number of decision trees combined into the model. More decision trees usually provide better fitting performance. Tree depth represents the complexity of one decision tree. Learning rate indicates how much portion of the result from each decision tree is combined into the final model. After the cross validation, the final model included 500 decision trees. The corresponding learning rate is 0.01, and tree depth is 3.

To interpret the model results, this study applied two tools. First, this study employed the SHapley Additive exPlanations (SHAP) value (Chen et al., 2022) to measure the contribution of independent variables. SHAP value is originated from the concept of Shapely value based on the cooperative game theory (Shapley, 1953). Generally, SHAP value measures the marginal impact of the inclusion of one independent variable on the prediction performance for each observation. A positive SHAP value indicates a positive impact and vice versa. In addition, the larger the absolute value of the SHAP value, the larger impact the corresponding independent variable has on prediction. The average absolute SHAP values of an independent variable for all observations is the contribution of the corresponding independent variable. Second, this study used the accumulated local effect (ALE) plots to visualize the nonlinear relationship between travel-related carbon emissions and independent variables. In addition, ALE plots (Apley & Zhu, 2020) were used to show the interactive impact between household income and built environment variables on travel-related carbon emissions. Compared with another commonly used tool, partial dependence plots, ALE plots are better in terms of their capability to handle multicollinearity among independent variables (Molnar, 2020).

4 Results

4.1 Variable contributions

Table 3 presents the contribution of each independent variable considered in this study. The SHAP value gauges the average absolute value of marginal impact when including the corresponding independent variable (i.e., built environment attribute or demographic variable) in predicting TCE for all individuals in the sample. The percentage indicates the proportion of the SHAP value of the independent variable among the sum of SHAP values of all independent variables. This study also ranked the independent variables based on their contributions and calculated the collective contributions in terms of percentage for built environment attributes and demographics, respectively.

Collectively, demographics make 60% of the contribution in estimating travel-related carbon emission, which is larger than that of built environment attributes (40%). This result shows that demographics play a more important role than the built environment in affecting people's TCE on weekdays.

Working status is the most important variable among all independent variables, with a SHAP value of 2.08. This result indicates that, on average, the marginal impact of being employed on TCE is 2.08 pounds. The second and third most important variables are job accessibility and gender, respectively. Household income has an SHAP value of 0.39, which is ranked eighth among all 16 variables considered in this study.

Table 3. Contributions of independent variables in predicting TCE

Type	Variable	SHAP value	Percentage	Ranking	Sum
Built environment attributes	**Job accessibility**	1.55	17.6%	2	40.0%
	Distance to St. Paul	0.46	5.2%	6	
	Distance to Minneapolis	0.45	5.1%	7	
	Transit stop density	0.38	4.3%	9	
	Intersection density	0.25	2.8%	11	
	Land use mix	0.23	2.6%	12	
	Population density	0.22	2.5%	14	
Demographic attributes	**Worker**	2.08	23.6%	1	60.0%
	Male	0.88	10.0%	3	
	Driving license	0.67	7.6%	4	
	Education level	0.55	6.3%	5	
	Household income	0.39	4.4%	8	
	Age	0.33	3.7%	10	
	Disability	0.22	2.5%	13	
	White	0.15	1.7%	15	
	Student	0.01	0.1%	16	

4.2 Main effects

This section presents the main effects of all built environment attributes and important demographics in terms of ALE plots. The ALE plot of an independent variable illustrates how its centered effect varies by its value. The centered effect is calculated by subtracting the average ALE value from each of the individual ALE values, which will shift the entire ALE curve so that its average effect is zero. Centering helps in emphasizing how the ALE values deviate from their average value. To facilitate the comparison across plots, this study applied the same scale of y axis for all ALE plots. The x axis represents the corresponding built environment attribute. The rugs on x axis show the distribution of the built environment attribute.

Figure 3 presents the relationship between TCE and the important built environment variables, including job accessibility, distance to St. Paul, distance to Minneapolis, and transit stop density. When the number of jobs with 20 minutes of driving is fewer than 800,000, job accessibility has a negative relationship with TCE. When job accessibility increases from 0 to approximately 800,000 jobs, it has a negative impact on TCE. This relationship is consistent with our expectation as people living in areas with higher job accessibility usually have shorter travel distances. However, after the threshold of 800,000 jobs, the impact becomes trivial, suggesting there is a threshold effect regarding job accessibility. In areas with job accessibility higher than 800,000 jobs, more people switch to biking and walking to reach their destination instead of driving and transit.

Distance to St. Paul has a reverse U-shape relationship with TCE. When distance to St. Paul increases from 0 to 15 miles, there is a fast-increasing trend. The city of St. Paul is one important job center in the Twin Cities area. For people living farther from it, their commuting distance becomes longer, and the associated driving or transit trips generate more carbon emissions. When the distance increases from 15 to 36 miles, the increase of this positive relationship becomes slower. This implies that the attraction of St. Paul becomes smaller in these areas and its influence on people's TCE starts to decrease. When the distance exceeds 36 miles, the relationship becomes negative. This might be because of the dual-center structure of Twin Cities and some of these areas are closer to the city of Minneapolis. People living in those areas choose to work in Minneapolis and have a lower level of TCE.

Distance to Minneapolis generally has a positive relationship with travel-related carbon emission. The reason for this positive relationship is similar to that of distance to St. Paul, i.e., the attraction of employment center. However, Minneapolis is the economic center of the Twin Cities area and, thus, has a stronger attractiveness than other employment centers in the area. This relationship becomes trivial when the distance exceeds 7 miles. Note that there is a negative impact when the distance starts to increase from 0. This negative relationship might be because people living in the downtown areas have more short trips and generate more TCE. This is consistent the result in Wu et al. (2019).

The relationship between transit stop density and travel-related carbon emission is U-shape. Initially, transit stop density is negatively associated with travel-related carbon emission, mainly due to the fact that transit travel modes (e.g., bus and light rail) are efficient in reducing TCE than driving. However, after transit stop density reaches about 40, it starts to become positively correlated with TCE. This positive relationship is mainly because that more transit trips are associated with more carbon emissions.

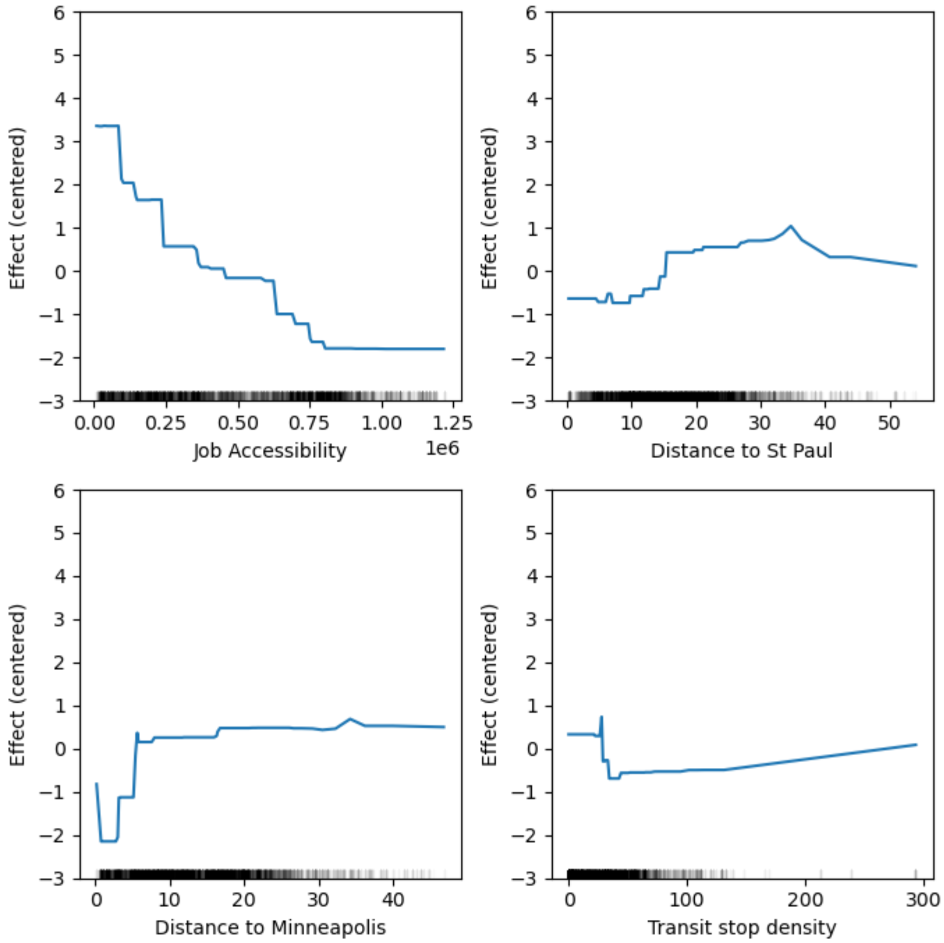

Figure 3. The relationships of important built environment variables

For other built environment variables with small contributions (Figure 4), their relationships are consistent with our expectation. Generally, intersection density, land use mix, and population density are all negatively correlated with TCE.

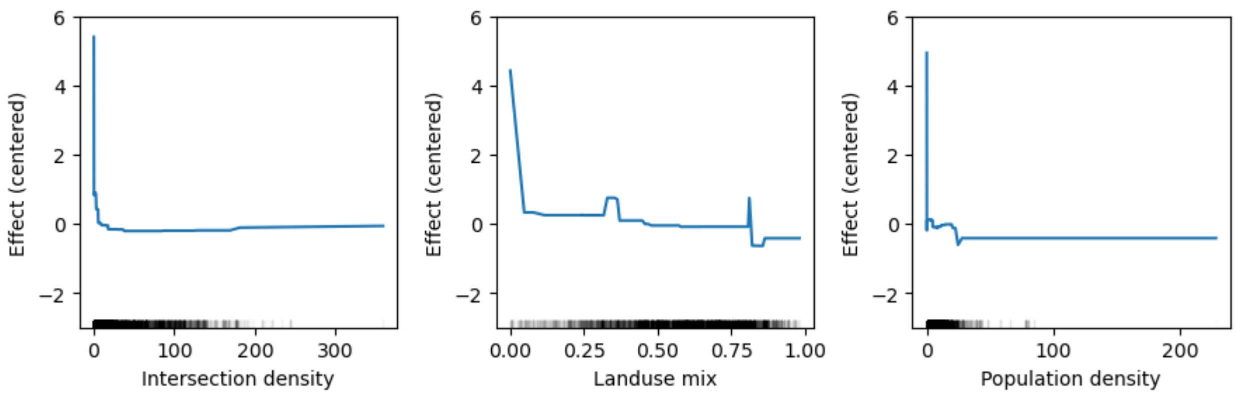

Figure 4. The relationships of other built environment variables

Figure 5 presents the relationships of important demographic variables, including employment status, gender, driving license, education level, household income, and age. Being employed, being male, and having a driver's license are all associated with a higher level of TCE. Education level is positively associated with TCE. Household income also has a positive relationship with TCE. However, this relationship becomes trivial when household income level exceeds 5 (i.e., 50,000 to 74,999 dollars). Age has a reverse U-shape relationship with TCE.

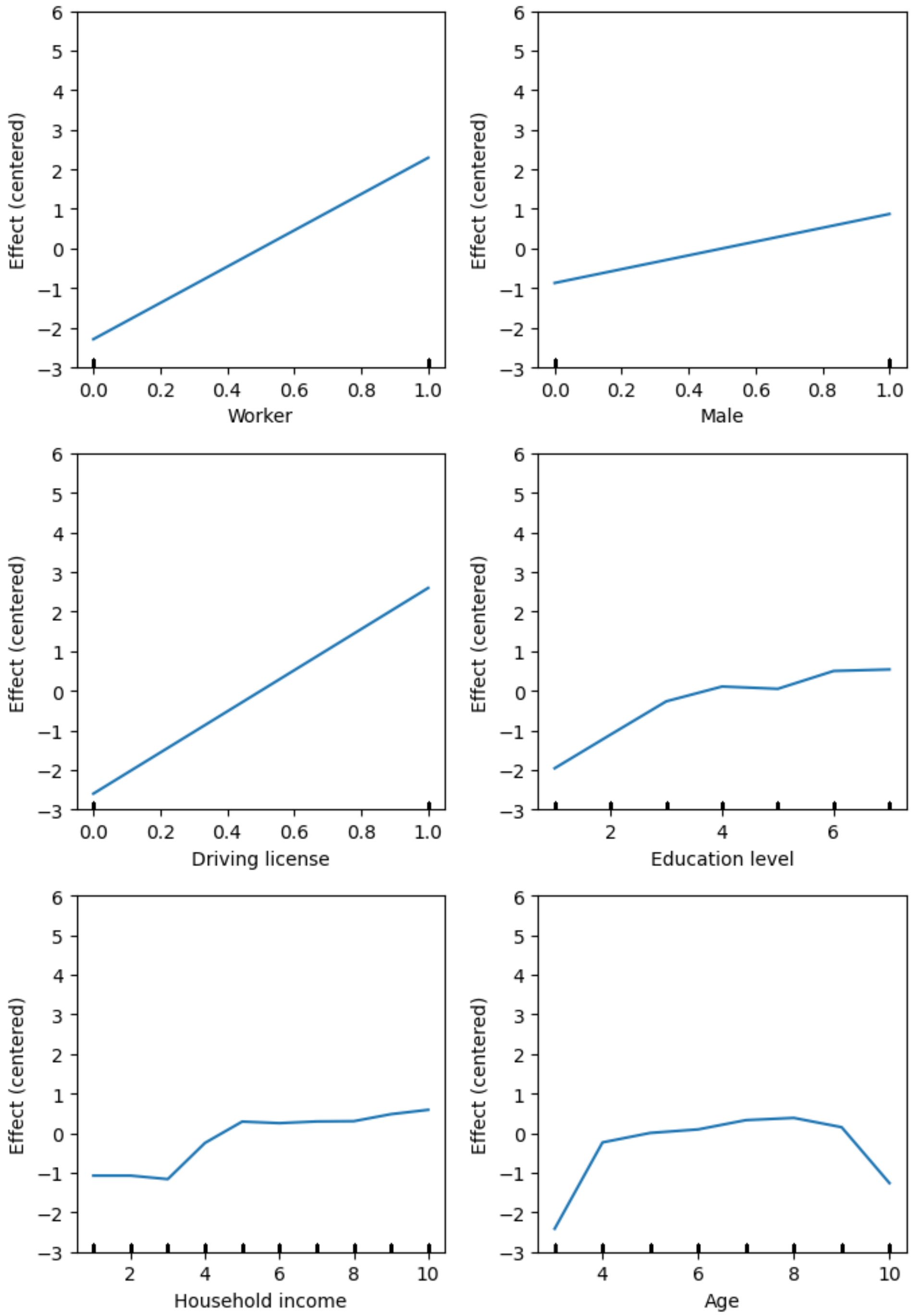

Figure 5. The relationships of important demographic variables

4.3 Interactive effect

This section presents the interactive effects between household income and important built environment variables on TCE. The interactive effects are shown as 3D ALE plots. The plot has three axes. The x axis represents household income. The y axis represents the built environment variable. The z axis presents the interactive effect of the two variables on TCE. Note that the interactive effect indicates the marginal effect generated by the interaction between the two variables and is not the sum of their main effects. To facilitate the readiness of the plots, this study used different colors to represent the value of the interactive effect. Darker red indicates a larger positive effect. Darker blue indicates a larger negative effect. White indicates no effect. This study also used the same scale of z axis for all plots to facilitate comparison across plots. One exception is the plot of household income and distance to St. Paul as their interactive effect is larger than other interactions.

Figure 6 presents the interactive effect between household income and job accessibility (in terms of million jobs within 20-minute driving) on TCE. There is a positive effect when both household income and job accessibility are in their lower values. This result shows that, for people with lower household income, when they live in the areas with lower job accessibility, they tend to generate extra travel-related carbon emission. For low-income population, they usually have much fewer choices in their jobs than high-income population. When there are fewer job opportunities they can access near their home locations, they are more likely to seek job opportunities in farther locations from their home. In addition, most low-income jobs provide limited options to work at home, which forces people to commute.

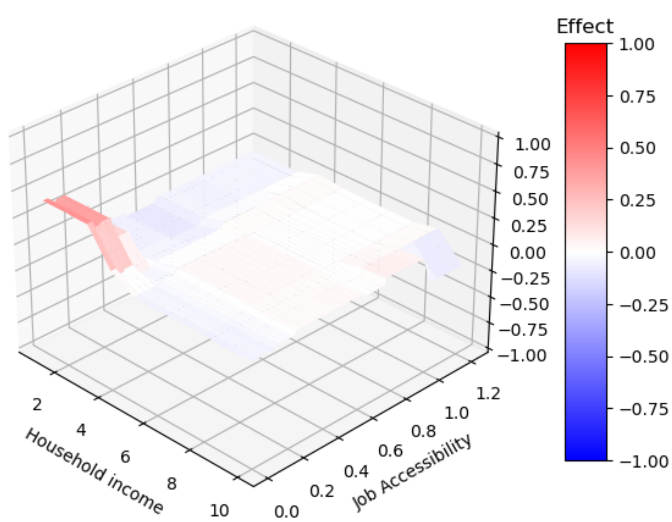

Figure 6. The interactive effects between household income and job accessibility

The interactive effect between household income and distance to St. Paul is shown in Figure 7. There is a positive impact in the area where household income is lower and distance to St. Paul is larger. For lower-income people, when they live in the areas farther from St. Paul, they tend to generate more TCE. Lower-income people have fewer opportunities to work at home (Tao & Cao, 2021) and are less likely to shop online (Cao et al., 2011; Saphores & Xu, 2021). They tend to make more trips for commuting and shopping trips compared with higher-income people when they are living farther away from the city center.

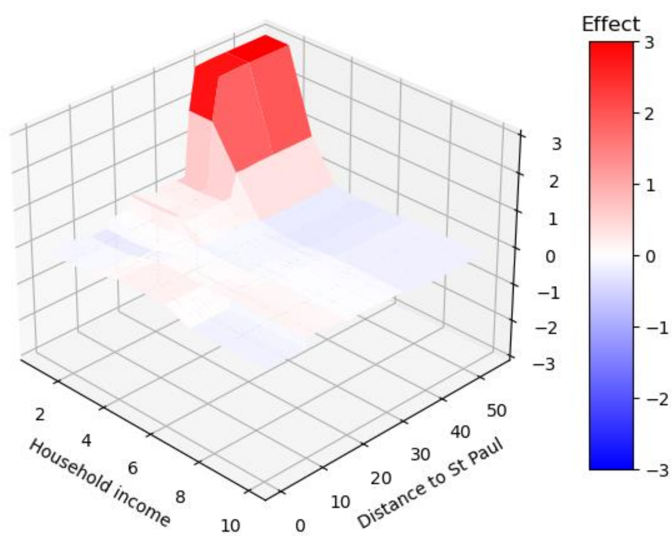

Figure 7. The interactive effects between household income and distance to St. Paul

Figure 8 presents the interactive effect between household income and distance to Minneapolis on TCE. The plot shows that, in downtown Minneapolis (i.e., distance to Minneapolis is very small), lower-income people tend to generate more TCE and higher-income people tend to produce less TCE. As the economic center of the Twin Cities area, there are many high-income jobs located in the downtown area of Minneapolis, such as banking, insurance, and consulting (MPLS Downtown Council, 2021). For higher-income people living in downtown

Minneapolis, they are more likely to find matched jobs and tend to have shorter trips. For lower-income people, they possibly have to seek jobs in other areas and tend to travel longer distances.

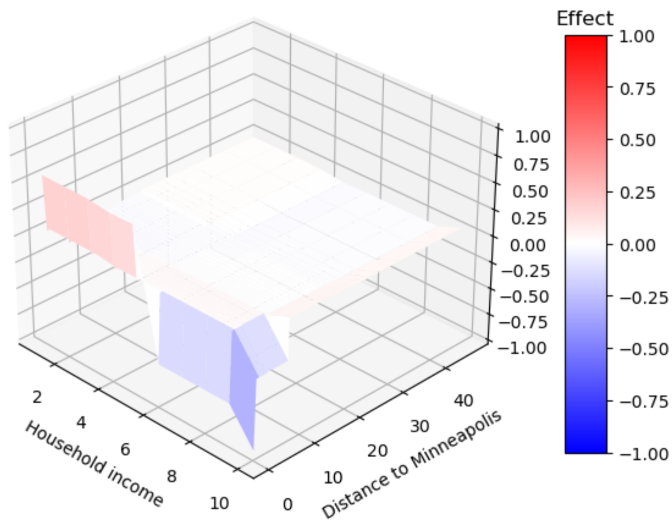

Figure 8. The interactive effects between household income and distance to Minneapolis

Finally, Figure 9 present the interactive effect between household income and transit stop density on TCE. When there is more transit supply near their home locations, lower-income people tend to have additional TCE while higher-income people tend to have less TCE. This difference is mainly because low-income people are captive transit riders and use more transit than high-income people. These additional transit trips generate more TCE.

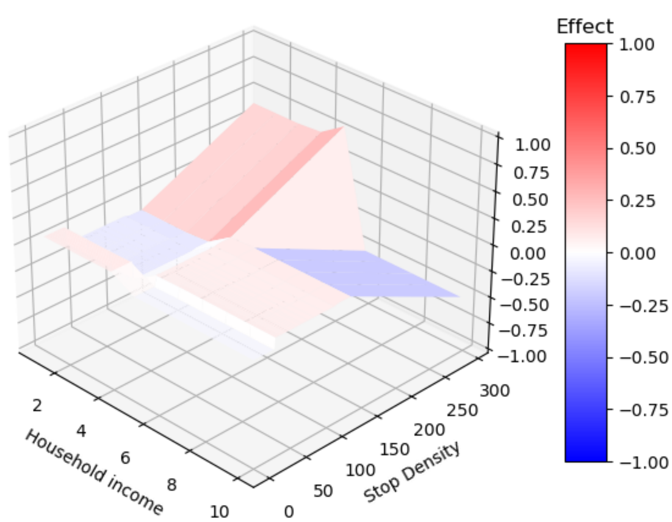

Figure 9. The interactive effects between household income and transit stop density

5 Conclusions

With the data from the Twin Cities area in US, this study employed the XGBoost approach to estimate the contributions of built environment attributes and demographics to predicting TCE and their nonlinear relationships. Besides the main effects, this study estimated the interactive effect between household income and important built environment variables on TCE.

Demographic variables collectively have a larger contribution than built environment attributes in estimating TCE. Individually, six demographic variables, including employment status, gender, a driver's license, education level, household income, and age, are among the ten most important variables according to their SHAP values. This result confirms the important role of demographics in influencing TCE. For built environment attributes, job accessibility, distance to St. Paul, distance to Minneapolis, and transit stop density are important variables, showing that distribution of job opportunities, the city structure, and transit supply are important in affecting people's TCE. Furthermore, the main effects show salient nonlinear relationships. The interactive effects suggest that additional impact on TCE could be produced when household income interacts with built environment attributes. There exist positive interactive impacts when lower-income people live in areas with lower job accessibility, farther from downtown St. Paul, in downtown Minneapolis, and with more transit supply. There are negative interactive impacts when higher-income people live in downtown Minneapolis and areas with more transit supply.

This study offers several important policy implications for creating sustainable and equitable transportation systems. First, more environment friendly and affordable transportation options, such as sharing electric vehicles, should be provided to low-income population, especially those living in areas with low job accessibility, downtown areas, and areas farther from the city center. One example is the Evie carsharing program in the Twin Cities[5]. This program started its operation in 2022 and provided all-electric and free-floating vehicles. This program offered discounted prices (i.e., Access PLUS) for the low-income population.

[5] Evie Carshare: https://eviecarshare.com/

Currently, the program covers the downtown area in Minneapolis, which could help address the additional TCE generated by low-income households living there. In the future, the program could cover more places with lower job accessibility and farther from the urban center.

Second, transit agencies should switch to using vehicles with clean energy such as electricity. Transit systems need more riders to ensure their efficiency in energy use and reduction in carbon emissions. However, transit ridership has been struggling in recent years in the US. For example, the transit ridership in the Twin Cities area has been decreasing since 2016 (Metro Transit, 2023). The pandemic also made another huge hit on the ridership. The energy consumption per passenger mile of the transit system has increased since then. The main result in this study showed that more transit supply is associated with more travel-related carbon emission. Furthermore, low-income people living in areas with more transit supply tend to produce additional carbon emissions via transit trips. Therefore, the local transit agencies should switch to vehicles with clean energy, such as electric vehicles. Electric vehicles are more efficient in energy use and could help significantly reduce carbon emissions. For example, the Zero-Emission Bus Transition Plan by the Metro Transit (2022) in the Twin Cities plans to replace 20% of its vehicles with electric ones.

Finally, more matched job opportunities should be provided to low-income people near their residential locations. The results of interactive effects showed that spatial mismatch forces the low-income population to seek jobs in areas farther from their home locations and make longer commuting trips. Providing matched employment opportunities near or in their residential areas could help shorten or even reduce these trips. This requires the coordination between different jurisdictions at the regional level to ensure that job opportunities and their nearby residents matched.

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