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Final Project Report

A Dynamic Analysis of the Built Environment-Travel Behavior Relationship Using Three Activity-Travel Surveys in the Austin, Texas Region

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16. Abstract

This study investigates the dynamic effects of the built environment on travel in Austin, Texas, over a 20-year period. Using three waves of household travel surveys from 1997, 2006, and 2017, the research employs a repeated cross-sectional approach to address the limitations of traditional longitudinal and cross-sectional studies, and to more accurately estimate effect sizes. Methodologically, we introduce a novel integration of machine learning and inferential modeling to uncover non-linear relationships and threshold effects of the built environment characteristics on travel. Using Gradient Boosted Decision Trees (GBDT) and Partial Dependence Plots (PDPs), we first identify optimal threshold points in the relationships, which are then incorporated into piecewise multilevel models.

Findings from the study reveal that the built environment serves as a sustainable tool for managing travel in the long term, contributing 50% or more to the total feature importance in predicting individual travel—surpassing the combined effects of personal and household characteristics. Improved transit accessibility, enhanced local and regional accessibility, higher population and employment densities, and greater diversity are all associated with significant reductions in travel—particularly within their identified thresholds—though the magnitude of their influence varies across time periods and shows diminishing marginal returns.

These findings highlight the potential of smart growth policies—such as expanding transit accessibility, promoting high-density and mixed-use development, and discouraging single-use development and peripheral sprawl—as effective strategies to reduce car dependency and manage travel demand. Moreover, the study demonstrates that the proposed integrated approach can effectively capture complex non-linear effects while enhancing flexibility and interpretability, reducing researcher bias, and enabling statistical inference—ultimately providing more robust and policy-relevant insights.

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EXECUTIVE SUMMARY

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INTRODUCTION

In the era of sustainable development, cities worldwide face challenges due to excessive car use. Despite goals to reduce car dependency, car usage continues to rise. To address this, research emphasizes reducing car use through concepts like new urbanism and smart growth, which promote high-density, compact, mixed-use, walkable, and transit-oriented development (Ewing & Cervero, 2010; Zhang, 2004). These approaches aim to reduce trip distances and encourage transit and active transportation, potentially decreasing car dependency and its associated issues, such as congestion, pollution, and inequity.

The relationship between the built environment and travel behavior has long interested researchers and practitioners in transportation, urban planning and design, health, and other fields. Research in the past three decades has accumulated voluminous publications on the subject matter. While a good portion of the existing literature concluded that the built environment could influence travel behavior, the reported findings on the magnitude of influence of the built environment on travel outcomes remain mixed. A meta-analysis of the existing literature by Stevens (2017) indicated that the impact of compact development on reducing driving is marginal, sparking debate among scholars (Clifton, 2017; Ewing & Cervero, 2017; Handy, 2017; Heres & Niemeier, 2017; Knaap et al., 2017; Manville, 2017; Nelson, 2017). Some of the key issues identified through this debate include the reliance on linear models and cross-sectional data, which may have underestimated the impact of the built environment on travel behavior in earlier studies (Clifton, 2017; Handy, 2017). Consequently, recent research has increasingly focused on exploring the non-linear nature of this relationship and utilizing data beyond a cross-sectional framework.

The primary objective of this study is to deepen the understanding of the relationship between the built environment and travel in Austin, TX, over a 20-year period. Utilizing three waves of household travel surveys from 1997, 2006, and 2017, this research uses a repeated cross-sectional approach to analyze the dynamics of the magnitude of the built environment's impact on vehicle miles traveled (VMT). Additionally, the study aims to apply a novel integrated machine learning and inferential modeling approach to explore non-linear relationships and identify threshold effects over time. Through this approach, this study intends to answer two main questions: (a) Can the built environment be sustained as a tool for controlling travel in the long term? and (b) How have the built environment-travel relationship and its magnitude evolved over the considered time?

Our study area, Austin, has experienced rapid growth and significant changes over the past three decades, with the population and employment nearly doubling. Notable changes include downtown growth, neighborhood infill and redevelopment, fringe expansion, and the expansion of the public transit network. Additionally, transit-oriented development and smart growth initiatives emerged after 2005. Overall, the extensive transformation of the built environment in Austin makes this study area ideal for such studies.

This study contributes significantly to the existing literature by uniquely integrating machine learning and traditional inferential modeling to explore non-linear relationships and identify threshold effects over a 20-year period, which clarifies the true nature of the relationship and leads to more reliable findings. Additionally, this study also contributes to deepening the theoretical understanding of the dynamic nature of the relationship by adopting a repeated cross-sectional approach in a rapidly growing city and highlighting the magnitude of the impact over time. Lastly, by focusing on VMT as a measure of travel behavior, the study provides valuable insights into how built environment factors influence travel demand and distance in the context of a U.S. city.

LITERATURE REVIEW

The current state of knowledge, challenges, and potential directions for research are discussed below.

Studies on non-linear relationship

Traditional inferential models have long served as the cornerstone for examining the relationship between the built environment and travel behavior. These models offer valuable insights into the magnitude and statistical significance of these relationships, providing interpretable coefficients and elasticities that are essential for policymaking. However, the assumption of linearity often oversimplifies the complex interactions between built environment factors and travel behavior, overlooking potential non-linear effects and threshold behaviors (Aghaabbasi & Chalermpong, 2023; Clifton, 2017; van Wee & Handy, 2016; Wu et al., 2019). Consequently, reliance on linear modeling can lead to inaccurate estimates, underestimating the true impact of the built environment factors. While non-linear regression models can capture non-linear relationships, their application is limited in the literature due to their reliance on assumptions and trial-and-error procedures for selecting functional forms or breakpoints, which risks introducing bias and misrepresenting relationships.

To address the limitations of linear models, recent studies have increasingly focused on the non-linear and threshold effects of the built environment on travel behavior, including mode choice (Ashik et al., 2024; Ding, Cao, & Wang, 2018; Hatami et al., 2023), driving distance (Ding, Cao, & Næss, 2018), driving (Hu et al., 2021; Zhang et al., 2022), and emissions (Shao et al., 2023; Wu et al., 2019). Machine learning methods have been widely applied to explore non-linearity and threshold effects (Aghaabbasi & Chalermpong, 2023; Ashik et al., 2024; Hatami et al., 2023; Hu et al., 2021; Shao et al., 2023). While machine learning can efficiently uncover non-linear relationships and threshold effects without relying on a priori assumptions, it lacks the ability to quantify the magnitude of these relationships or provide measures of statistical significance, which limits its explanatory power and policy relevance (Ding, Cao, & Wang, 2018; Shao et al., 2023; Wu et al., 2019). Moreover, distinguishing between true non-linear effects and spurious patterns caused by random noise or chance correlations remains a challenge.

Therefore, a novel framework is needed that combines the strengths of both machine learning and traditional inferential modeling to overcome the limitations inherent in applying each method separately. This integrated dual-method approach could not only enhance the robustness of the analysis but also improve interpretability, enabling more nuanced and actionable insights into the relationship between the built environment and travel behavior.

Studies on multi-period data

Cross-sectional studies provide valuable insights into the correlational relationship between the built environment and travel behavior at specific points in time. However, they are limited in establishing causality and accurately quantifying impact magnitude (Clifton, 2017; Coevering et al., 2016; Handy et al., 2005). Additionally, machine learning studies exploring non-linearity often rely on single datasets or time periods, raising concerns about the stability and consistency of their findings across time or beyond a specific dataset (Wang & Cheng, 2020).

Studies using multi-period data (longitudinal data) can address these limitations by offering a more comprehensive view over time, though such data are challenging to obtain, particularly at a disaggregated level. Some studies have utilized multi-period data, which can generally be categorized into two types: a) panel data studies and b) household relocation studies.

A few disaggregated studies have attempted to conduct longitudinal research by utilizing panel data (Coevering et al., 2016; Gao et al., 2019; Kamruzzaman et al., 2016; Rahman, 2023; van de Coevering et al., 2021). These studies use panel survey data from the same samples across multiple periods (generally two waves), usually with short intervals (less than 10 years), to estimate the association between certain aspects of the built environment and travel behavior, while controlling for factors like travel attitudes and socio-demographics. However, panel data studies face limitations, such as the overrepresentation of wealthy and educated samples, stagnation effects, and the relative stability of the built environment and travel behavior over short periods in developed countries. They also struggle to account for changes in travel behavior due to life events and other external variables, leading to potential inaccuracies. While panel data can help establish causality, these studies provide limited insights into the magnitude of relationships due to the frequent use of structural equation modeling (SEM) techniques and other aforementioned limitations.

On the other side, some studies focus on household relocation and use quasi-longitudinal data from individuals who have recently moved (Cao et al., 2007; De Vos, Cheng, Kamruzzaman, et al., 2021; De Vos, Cheng, & Witlox, 2021; De Vos et al., 2018; Handy et al., 2005, 2006; Krizek, 2000, 2003; Milakis et al., 2017; Wang & Lin, 2019; Wells & Yang, 2008). These studies assume that changes in residential location also lead to changes in the built environment and, subsequently, affect travel behavior. However, these studies are retrospective, relying on memory and using imprecise indicators, which could affect reliability and accuracy of the findings. While they help in understanding causal relationships, they often struggle to quantify the magnitude of the built environment's effects on travel behavior due to the imprecise nature of the data and the frequent use of SEM-based analysis methods.

Besides these two types of studies, a third type of longitudinal study is rarely found in literature. This type, known as a repeated cross-sectional study, is a "pseudo-longitudinal" type of data that combines data from two cross-sectional household travel surveys conducted at different points in time to create a multi-period dataset (Grunfelder & Nielsen, 2012; Zhang & Zhang, 2015). Although this type of study can estimate the magnitude of impacts more accurately, previous studies typically cover a short period (less than 10 years). Generally, the built environment characteristics and travel behavior remain stable over such short periods in developed cities.

Summary

In summary, while longitudinal studies help establish causal relationships, they often fall short in providing reliable evidence on the magnitude of impacts due to inherent limitations. Moreover, to our knowledge, no comprehensive studies examining the non-linear relationships and threshold effects of the built environment on travel behavior have utilized multi-period data. To improve the generalizability of findings and to better understand the dynamics of non-linear and threshold effects, it is essential to analyze these relationships across multiple time periods and datasets. Therefore, studies incorporating more than two waves of data over extended timeframes (e.g., 20 years) in rapidly growing cities—where substantial changes in the built environment occur—are needed to more accurately assess the magnitude and threshold effects of the built environment's impact on travel behavior.

DATA

Data preparation

Data Sources and Study Area

To conduct this study, we collected data of three household travel surveys conducted in 1997, 2006, and 2017 in the Austin, Texas region from the Capital Area Metropolitan Planning Organization (CAMPO). These surveys covered a large, randomly selected number of households within the Austin region and collected all trip data for all household members during a workday. Although the study area coverage varied across the three surveys, all three consistently included the counties of Travis, Williamson, and Hays. To maintain consistency across the three time periods, we only considered household data from these three counties. A map of the study is presented in **Figure 1**.

Estimation of Vehicle Miles Traveled (VMT)

In this study, our dependent variable is individual daily VMT. For the 2006 and 2017 travel surveys, origin and destination coordinates were available for all trips. However, for the 1997 data, precise origin and destination coordinates were not provided. Instead, traffic analysis zone (TAZ) IDs for the trip origins and destinations were available. Using the spatial file for the 1997 TAZs, we estimated the coordinates of each TAZ based on its centroid. These estimated TAZ-specific coordinates were then used as coordinates for the origin and destination of the corresponding trip.

Using data of the trip coordinates, we estimated person miles traveled (PMT) for all trips using the shortest route distance technique in TransCAD software. From PMT, we estimated VMT using the mode of transportation information. If a person made a trip using any personal motorized vehicle, such as a car, motorcycle, van, jeep, etc., the PMT was considered the VMT for that person. We then aggregated the VMT of all trips for each person to estimate their total daily VMT, which is the dependent variable of our study. We removed data of an individual from the sample if they traveled outside the study area, as accurate origin and destination coordinates or information for external areas were unavailable in the surveys, and road network information outside the study area was not available. Only a small number of records (~5% of the overall sample) were removed through this process.

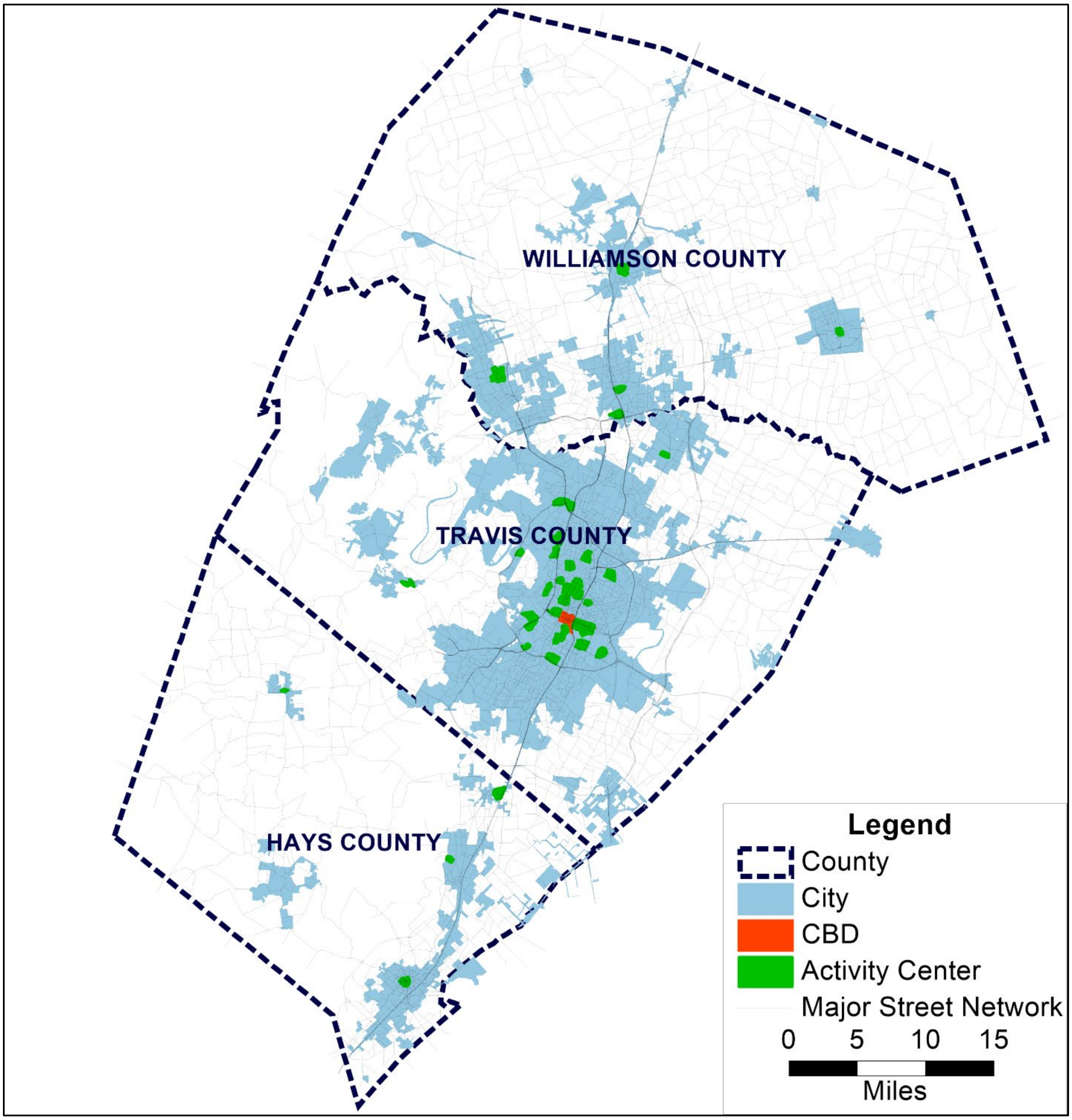

Figure 1: Study Area

To assess whether the centroid-based approach for measuring trip distance used for the 1997 survey might produce different VMT estimates, we conducted a robustness check using the 2006 and 2017 datasets. Specifically, we re-estimated VMT in those years using TAZ centroids (as was done for 1997) and compared the results with those derived from the precise coordinate-based method. The findings indicate that while the centroid method slightly overestimates average VMT, the difference is minor (less than 1 VMT) and not practically significant. Additionally, the correlation between VMT values derived from the two methods was greater than 0.9 in both years, indicating strong consistency. These results suggest that the use of TAZ centroids in 1997 does not meaningfully distort VMT measurement.

Personal and Household Characteristics

In the case of explanatory variables, data related to personal and household characteristics for each individual were available in the household travel surveys. Summary statistics of this data are presented in **Table 1**. Residential self-selection is a widely discussed factor in the literature that must be controlled to address endogeneity and accurately estimate the built environment's impact on travel behavior (Ewing & Cervero, 2010; Wang & Lin, 2019; Zhang & Zhang, 2020). Following the method of Zhang & Zhang (2020) and Zhang & Zhang (2015), we aim to control the effect of residential self-selection using a variable named HH_Selection, which indicates the factors influencing the respondent’s current household location choice. This variable is classified as an access factor if the household location choice is influenced by proximity to work, school, or public transportation; otherwise, it is considered a non-access factor.

Built Environment Characteristics

For built environment characteristics data, previous studies have considered a wide range of indicators, especially those representing the 5Ds: density, diversity, design, distance to transit, and destination accessibility (Ewing & Cervero, 2010; Handy, 2017; Nelson, 2017). Since we needed consistent data for all three years, we faced limitations in selecting a wide variety of built environment factors. We had TAZ spatial boundaries and corresponding population and employment data for all three years, which were collected from the CAMPO. Therefore, we were able to incorporate TAZ-level population density and employment density for all three years.

We were unable to collect land use data for all three years for the entire study area. So, we could not include land use diversity. However, we did have disaggregated TAZ-level employment data for basic, retail, and service sectors, as well as household data. Using this information, we estimated TAZ-level 3-tier employment (basic, retail, and service) and household entropy. This was considered the diversity variable in this study. The equation for diversity calculation is presented below.

$$\text{Diversity} = -\frac{\frac{\text{HH}}{\text{TA}} \cdot \ln\left(\frac{\text{HH}}{\text{TA}}\right) + \frac{\text{BE}}{\text{TA}} \cdot \ln\left(\frac{\text{BE}}{\text{TA}}\right) + \frac{\text{RE}}{\text{TA}} \cdot \ln\left(\frac{\text{RE}}{\text{TA}}\right) + \frac{\text{SE}}{\text{TA}} \cdot \ln\left(\frac{\text{SE}}{\text{TA}}\right)}{\ln(4)}$$

Here, HH = Number of households in the TAZ, BE = Number of basic employment in the TAZ, RE = Number of retail employment in the TAZ, SE = Number of service employment in the TAZ, and TA = Total employment plus number of households.

Then, based on the geographic coordinates of each individual's household location, we identified the corresponding TAZ. We then attached TAZ-level population density, employment density, and diversity data to each corresponding individual.

In addition, we incorporated distance to transit related built environment characteristics by estimating the distance to the nearest transit stop from each individual's household location. Since we were unable to collect transit stop data for 1997, we estimated this indicator based on transit stop location data from 2003, assuming that the number and locations of transit stops were relatively stable between 1997 and 2003. Although this assumption may not be perfectly precise, it is reasonable given that the transit network in Austin expanded significantly after 2006. Therefore, we do not expect this to cause significant errors in the modeling process.

Additionally, we considered distance to the Central Business District (CBD) and distance to the nearest activity center to address the regional and local destination accessibility dimensions of the built environment, respectively. Austin is a monocentric city with a single downtown area. Thus, the distance to the CBD was estimated as the distance from each household location to downtown. In contrast, in 2005, the City of Austin identified activity centers in the Austin region. Using these locations, we estimated the distance from each household location to the nearest activity center. In this way, we tried to minimize data limitations and incorporated relevant built environment characteristics to achieve a comprehensive and robust result. Summary statistics of built environment characteristics are presented in **Table 1**.

Table 1: Variable Description and Sample Statistics

Variable Code	Variable Description		Descriptive Statistics[1]		
			1997	2006	2017
Dependent Variable					
VMT_Person	Individual daily vehicle miles traveled (VMT)		23.71 (33.9)	20.28 (21.4)	19.25 (19.4)
Explanatory Variables					
Personal characteristics related variables					
Sex	Sex of the respondent	Female*	51.3%	52.5%	53.7%
		Male	48.7%	47.5%	46.3%
Ethnicity	Race or ethnicity of the respondent	Non-white/ Caucasian*	29.3%	32.6%	34.3%
		White/Caucasian	70.7%	67.4%	65.7%
Age	Age of the respondent in years		32.26 (20.5)	37.56 (23.7)	37.15 (22.8)
Disability	Whether the respondent has a transportation disability	No*	95.1%	95.5%	95.5%
		Yes	4.9%	4.5%	4.5%
Licensed_Driver	Whether the respondent is a licensed driver	No*	30.5%	32.6%	30.1%
		Yes	69.5%	67.4%	69.9%
Work_Hr_Wkly	Number of hours respondent worked weekly		20.20 (20.8)	16.05 (20.7)	18.24 (20.5)

Variable Code	Variable Description		Descriptive Statistics[1]		
			1997	2006	2017
Flex_Time	Whether the respondent's work hours are flexible	Unemployed*	46.9%	59.2%	52.1%
		Fixed	28.4%	24.0%	27.9%
		Flexible	24.7%	16.8%	20.0%
Home_Office_Wkly	Number of days respondent worked from home weekly		0.13 (0.7)	0.27 (1.1)	0.43 (1.3)
Student	Whether the respondent is a student	No*	67.0%	73.8%	70.6%
		Yes	33.0%	26.2%	29.4%
Household characteristics related variables					
HH_Size	Number of persons living in the respondent's household		3.26 (1.5)	3.53 (1.7)	3.23 (1.4)
No_Employed	Number of employed persons living in the respondent's household		1.56 (0.9)	1.36 (0.9)	1.46 (0.9)
No_Vehicle	Number of motorized vehicles available in the respondent's household		1.96 (0.9)	2.02 (0.9)	2.05 (0.9)
No_Bike	Number of bicycles available in the respondent's household		1.41 (1.6)	1.46 (1.7)	1.49 (1.7)
HH_Selection	Factors influencing the respondent's current household location choice	Non-access factor*	86.1%	72%	66.9%
		Access factor	13.9%	28%	33.1%
HH_Income	Yearly income of all members of the respondent's household ($ thousand)		46.27 (33.5)	59.21 (42.0)	81.76 (55.1)
Built environment characteristics related variables					
Household level variables					
Dist_transit	Distance from respondent's household location to the nearest transit stop in miles		3.61 (6.1)	3.56 (5.7)	0.89 (1.1)
Dist_CBD	Distance from the respondent's household location to the downtown (CBD) in miles		10.40 (8.5)	11.89 (8.6)	10.45 (6.9)
Dist_Actvy_Center	Distance from respondent's household location to the nearest activity center in miles		2.52 (2.3)	3.15 (2.7)	3.10 (2.2)
TAZ level variables					
PopDEN	Population density in the respondent's household TAZ (persons/acre)		5.46 (5.0)	5.44 (4.4)	6.41 (5.8)
EmplyDEN	Employment density in the respondent's household TAZ (jobs/acre)		2.23 (7.0)	1.80 (4.1)	2.85 (15.7)
Diversity	3-tier employment (basic, retail, and service) and household entropy		0.56 (0.2)	0.58 (0.2)	0.55 (0.2)
Sample Size					
Individual Sample			4459	3020	6252
Household Sample			1854	1128	2459

* These values of the categorical variables are designated as the reference category for modeling purposes.

[1] For categorical variables, percentages are provided. For numeric variables, the table shows means and standard deviations (in brackets).

Sample Characteristics

In total, we processed data for 4459, 3020, and 6252 individuals from 1854, 1128, and 2459 households for the years 1997, 2006, and 2017, respectively. Travis County accounted for the majority of surveyed households in all three waves—74.7% in 1997, 65.6% in 2006, and 78.2% in 2017. Williamson County's share rose from 13.4% in 1997 to 26.2% in 2006, before declining to 16.6% in 2017. Hays County, meanwhile, saw a gradual decrease from 12.0% to 5.2% over the same period. These figures reflect moderate variation in household distribution across counties but do not suggest any substantial shifts that would raise concerns about compositional bias.

Based on the sample characteristics provided in **Table 1**, the average daily VMT of individuals was the highest in 1997 and significantly decreased by 2006. In 2017, the average daily VMT was slightly lower than in 2006. This reduction in VMT may be attributed to a combination of three key factors: a) statewide travel trends in Texas showed a modest decline in VMT per capita beginning in the early 2000s, which aligns with the observed pattern (Davis, 2019); b) VMT estimates for 1997 may be marginally inflated due to the use of centroid-based estimation in the absence of precise trip coordinates; and c) differences in sample composition, particularly age distribution and workforce characteristics. Specifically, the 1997 sample was considerably younger than those in 2006 and 2017. Additionally, the 1997 sample had a higher proportion of individuals in the working group who were less likely to work from home compared to the samples from 2006 and 2017. These demographic differences likely contributed to higher travel demand in 1997. In contrast, other variables related to personal characteristics exhibited roughly similar distributions across the three time periods.

Regarding household characteristics, the number of motorized vehicles and bicycles in households increased over time. In 1997, only 13% of the sample chose their household location based on access-related factors. This percentage increased to 28% in 2006 and 33% in 2017, indicating that more people chose their household location based on access-related factors in the later years. Household income was also higher in the later years, which may indicate higher-income samples in those years and/or the effects of inflation.

Focusing on built environment factors, there was a significant reduction in the average distance to the nearest transit stop, which decreased from 3.56 miles in 2006 to 0.9 miles in 2017, suggesting a substantial expansion of the transit network between these years. Regarding the distance to the CBD and the nearest activity center, the 2006 sample lived relatively farther from these locations, which is also reflected in its employment density. Although employment in the overall study area increased by 1.36 times from 1997 to 2006, the average TAZ-level employment density at the respondents' household locations decreased from 2.23 jobs per acre in 1997 to 1.8 jobs per acre in 2006. This decrease in employment density in 2006 compared to 1997 might be explained by households being located further from major employment centers. In 2017, both population and employment densities were higher than in the previous years. Lastly, the diversity index was relatively consistent across all three years.

ANALYSIS AND RESULTS

In this study, we aim to integrate machine learning and inferential modeling techniques. More specifically, we first explored the non-linear relationships between built environment factors and individual daily VMT using explainable machine learning (XML) methods, as these techniques are highly effective at identifying complex, non-linear relationships without requiring presuppositions or pre-defined functional forms. This exploratory step allowed us to identify key breakpoints (thresholds) in the relationship, enabling a data-driven understanding of non-linear patterns. We then incorporated these breakpoints into inferential models to estimate the magnitude and statistical significance of the non-linear relationships. While machine learning excels at uncovering flexible patterns in data, it does not provide direct estimates of effect sizes or significance levels—critical elements for policy-relevant interpretation.

Our integrated approach addresses the limitations of both standalone methods. Machine learning models, though powerful in predictive accuracy and flexibility, often lack interpretability and inferential transparency, making them less suitable for drawing actionable conclusions in planning and policy contexts (Ding, Cao, & Wang, 2018; Shao et al., 2023; Wu et al., 2019). Conversely, traditional non-linear inferential methods offer statistical rigor but rely on strong assumptions about functional forms and breakpoint locations—often determined through trial-and-error (iterative process) to optimize model fit—thereby increasing the risk of researcher bias and potentially misrepresenting the underlying non-linear patterns. By using machine learning outputs to guide the specification of non-linear forms in inferential models, our integrated method ensures both data-driven flexibility and explanatory clarity. This approach enhances model accuracy and replicability, minimizes bias, and improves the practical relevance of the findings for urban policy applications.

Before developing the models, we checked and addressed missing values and outliers in the three datasets. We also assessed multicollinearity among the explanatory variables using variance inflation factor (VIF) statistics. All the VIF values for the three datasets were found to be less than 5, indicating that multicollinearity was not an issue. In terms of modeling, we first conducted machine learning analyses and then, based on the findings from these models, performed inferential analyses, which we discuss below. A graphical presentation of the modeling approach is presented in **Figure 2**.

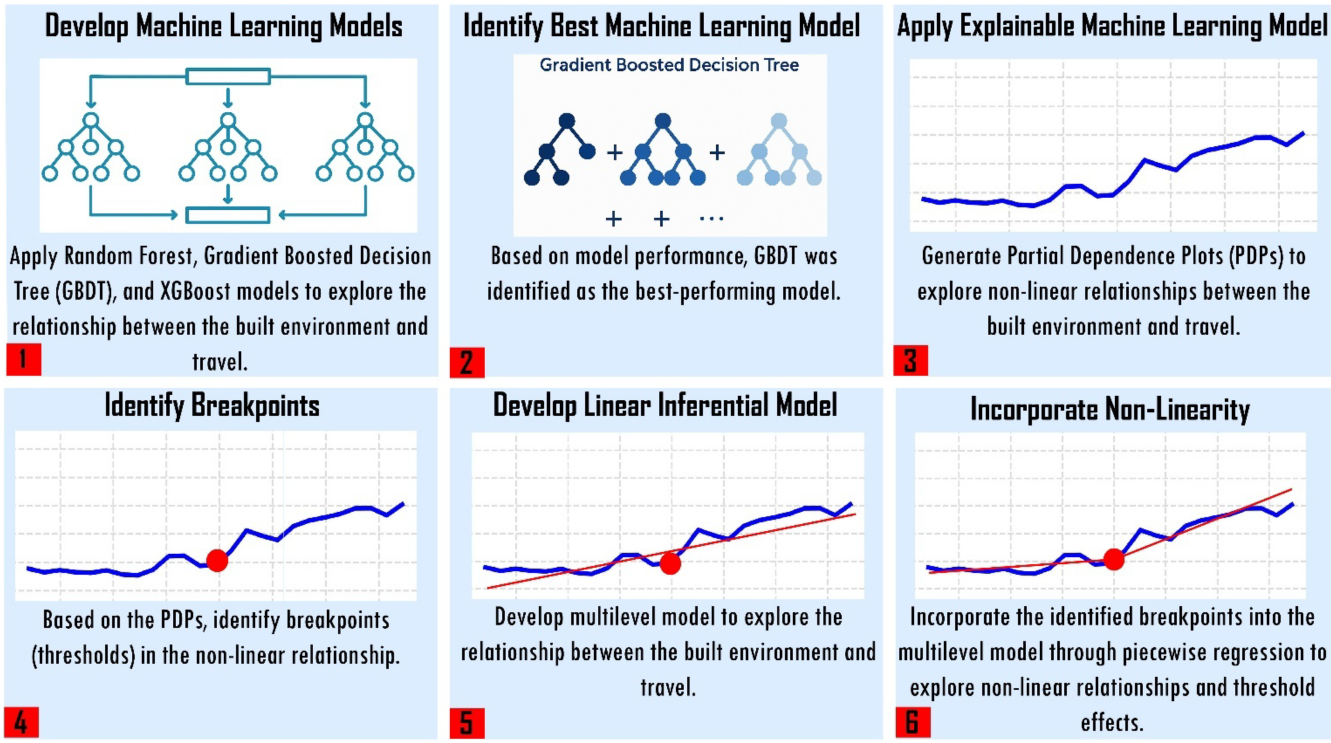

Figure 2: Modeling Approach

Machine Learning

Overview of Machine Learning Methods

In recent travel behavior studies—such as those investigating driving, mode choice, emissions, and transit ridership—Random Forest (RF) and Gradient Boosted Decision Trees (GBDT) are among the most widely used machine learning techniques, particularly for exploring non-linear relationships (Aghaabbasi & Chalermpong, 2023; Ashik et al., 2024; Cheng et al., 2019; Ding, Cao, & Næss, 2018; Hatami et al., 2023; Li & Kockelman, 2022). Both models are ensemble learning techniques that generate results by constructing multiple decision trees to improve predictive performance. RF is a bagging method that uses bootstrapping to resample the original data and trains multiple decision tree models on different subsets of the data, which helps reduce variance and prevent overfitting (Cheng et al., 2019). In contrast, GBDT is a boosting method that sequentially builds decision tree models, each focusing on correcting the errors of the previous model, thereby improving model accuracy and reducing bias (Ding, Cao, & Næss, 2018). Both techniques are highly efficient at handling large datasets and uncovering complex, non-linear relationships.

Additionally, we identified a recent algorithm called Extreme Gradient Boosting Model (XGBoost), an advanced variant of boosting technique, which is relatively new in travel behavior studies but may have the potential to perform as well as, or even better than, GBDT. Therefore, in our study, we utilized three machine learning algorithms—RF, GBDT, and XGBoost—to predict individual daily VMT, estimate the relative contribution of each explanatory factor, and explore the non-linear relationships between built environment factors and individual daily VMT.

Model Development and Optimization

To develop and assess the machine learning models, we first split our datasets into training and testing sets, with 20% of the data reserved for testing. A total of nine machine learning models were developed using the three algorithms (RF, GBDT, and XGBoost) across three separate datasets corresponding to the years 1997, 2006, and 2017. These models were implemented in Python using the scikit-learn library. To optimize the performance of these models, hyperparameters were tuned using GridSearchCV. The search ranges for hyperparameter optimization and the optimal hyperparameters identified are presented in **Table 2**. The tuning process was based on minimizing mean squared error (MSE) statistics, and a five-fold cross-validation (CV) procedure was applied.

Model Performance Evaluation

After developing the models, we calculated the root mean squared error (RMSE) and R^2 statistics for each model to evaluate their performance (**Table 2**). A model is considered superior if it exhibits a lower RMSE and a higher R^2 compared to the others. Our results indicate that while the RF algorithm performs comparably to the GBDT algorithm, the GBDT slightly outperforms RF across all cases. Conversely, XGBoost did not perform as well as the other two algorithms. Consequently, we identified GBDT algorithm as the best-performing machine learning technique for this study. Among the GBDT models, the R^2 statistics were the highest for the models corresponding to the years 1997 and 2006 (33%), while the model for 2017 showed a slightly lower R^2 of 29% (**Table 2**). This suggests that the explanatory variables account for approximately 33% of the variance in individual daily VMT for the years 1997 and 2006, and 29% for the year 2017.

Using XML to Explore Feature Importance and Non-Linear Relationships

XML refers to a class of techniques designed to interpret and visualize the outputs of complex machine learning models, often referred to as "black-box" models. These methods aim to reveal how individual input features influence model predictions, making the results more transparent and suitable for interpretation in applied research contexts. In our study, we employed XML tools to better understand the relationships between explanatory variables and individual daily VMT.

Given that the GBDT algorithm proved to be the most effective for our data, we conducted feature importance analysis—a commonly employed XML tool—using the GBDT models to rank explanatory variables by their contributions to predicting individual daily VMT across all three years (**Figure 3**).

To investigate the non-linear relationships between the dependent variable and explanatory variables, visualization-based XML tools—Partial Dependence Plots (PDP) and Accumulated Local Effects (ALE) plots— are commonly used in literature (Ashik et al., 2024; Ding, Cao, & Næss, 2018; Shao et al., 2023). Both methods have their own advantages and disadvantages: while PDPs are straightforward to compute and interpret, they do not perform well when multicollinearity is present among explanatory variables (Shao et al., 2023; Zhang et al., 2022). On the other hand, ALE plots are more robust to multicollinearity but can be more challenging to interpret (Ashik et al., 2024; Shao et al., 2023).

Since multicollinearity was not detected among our explanatory variables, we chose to explore the non-linear relationships between the explanatory variables—including built environment factors—and the dependent variable by generating PDPs based on the GBDT models. **Figures 4** and **5** illustrate the non-linear relationships between built environment factors and travel, while **Appendix A** presents rug plots showing the non-linear relationships for all numeric explanatory variables. A detailed interpretation and discussion of **Figures 3**, **4**, and **5** are provided in **Section 4.2**.

Table 2: Hyperparameter Tuning and Performance of the Models

Model Type	**Hyperparameter Optimization**		**1997**	**2006**	**2017**
	Hyperparameter	**Search Range**			
Random Forest	Number of trees	100-1200	300	1000	1000
	Maximum depth	1-20	9	15	15
	Maximum features	'auto', 'sqrt', 'log2', None	'sqrt'	'sqrt'	'sqrt'
GBDT	Number of estimators	100-1200	550	1000	1000
	Learning rate	0.001-0.1	0.01	0.01	0.01
	Maximum depth	1-20	5	7	7
	Maximum features	'auto', 'sqrt', 'log2', None	'sqrt'	'sqrt'	'sqrt'
	Subsample	0.5-1.0	0.9	0.8	0.9
XGBoost	Number of estimators	100-1200	300	700	200
	Learning rate	0.001-0.1	0.02	0.075	0.05
	Maximum depth	1-20	4	3	6
	Minimum child weight	1-10	6	7	6
	Subsample	0.5-1.0	1.0	1.0	0.9
	Column sample by tree	0.5-1.0	0.9	0.7	0.9
	Gamma	0-0.5	0.0	0.0	0.1
Performance Evaluation					
Random Forest	RMSE		28.58	17.12	17.53
	R^2		0.32	0.32	0.26
GBDT	RMSE		28.40	17.02	17.17
	R^2		0.33	0.33	0.29
XGBoost	RMSE		28.61	17.76	17.37
	R^2		0.32	0.27	0.27

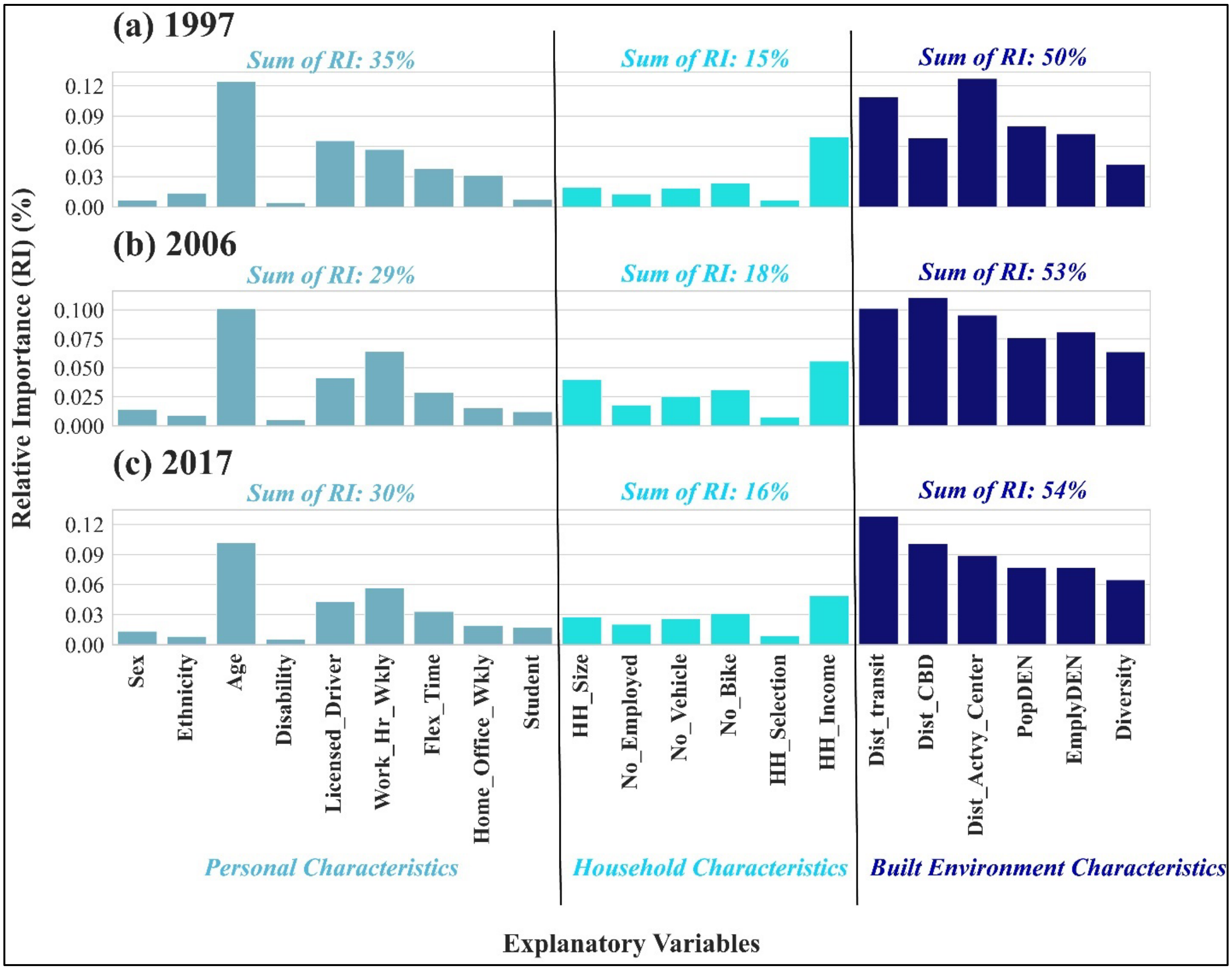

Figure 3: Relative Importance of the Explanatory Variables to Explain Individual Daily VMT (VMT_Person)

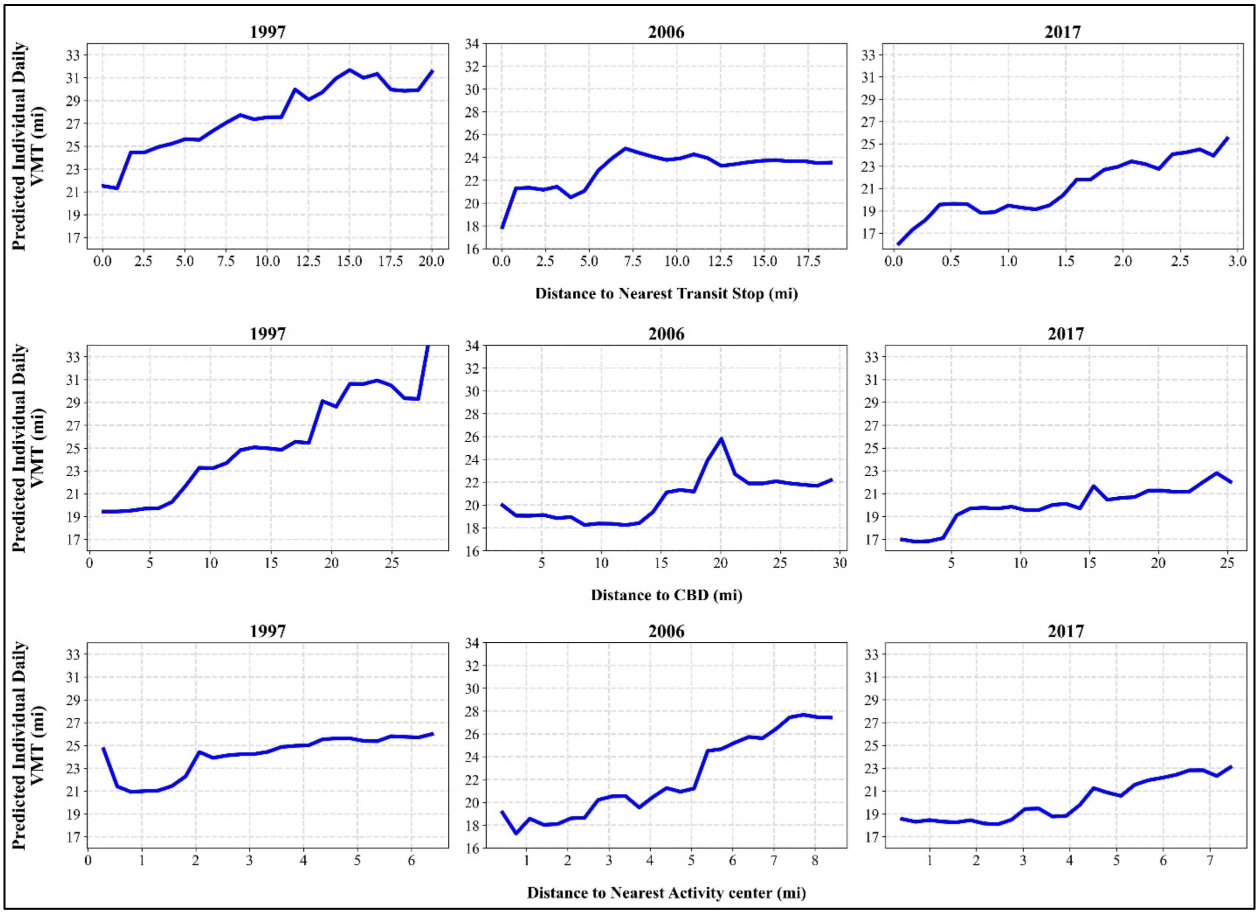

Figure 4: Non-linear Effects of Distance to Nearest Transit Stop (Dist_transit), Distance to CBD (Dist_CBD), and Distance to Nearest Activity Center (Dist_ Actvy_Center) on Individual Daily VMT (VMT_Person)

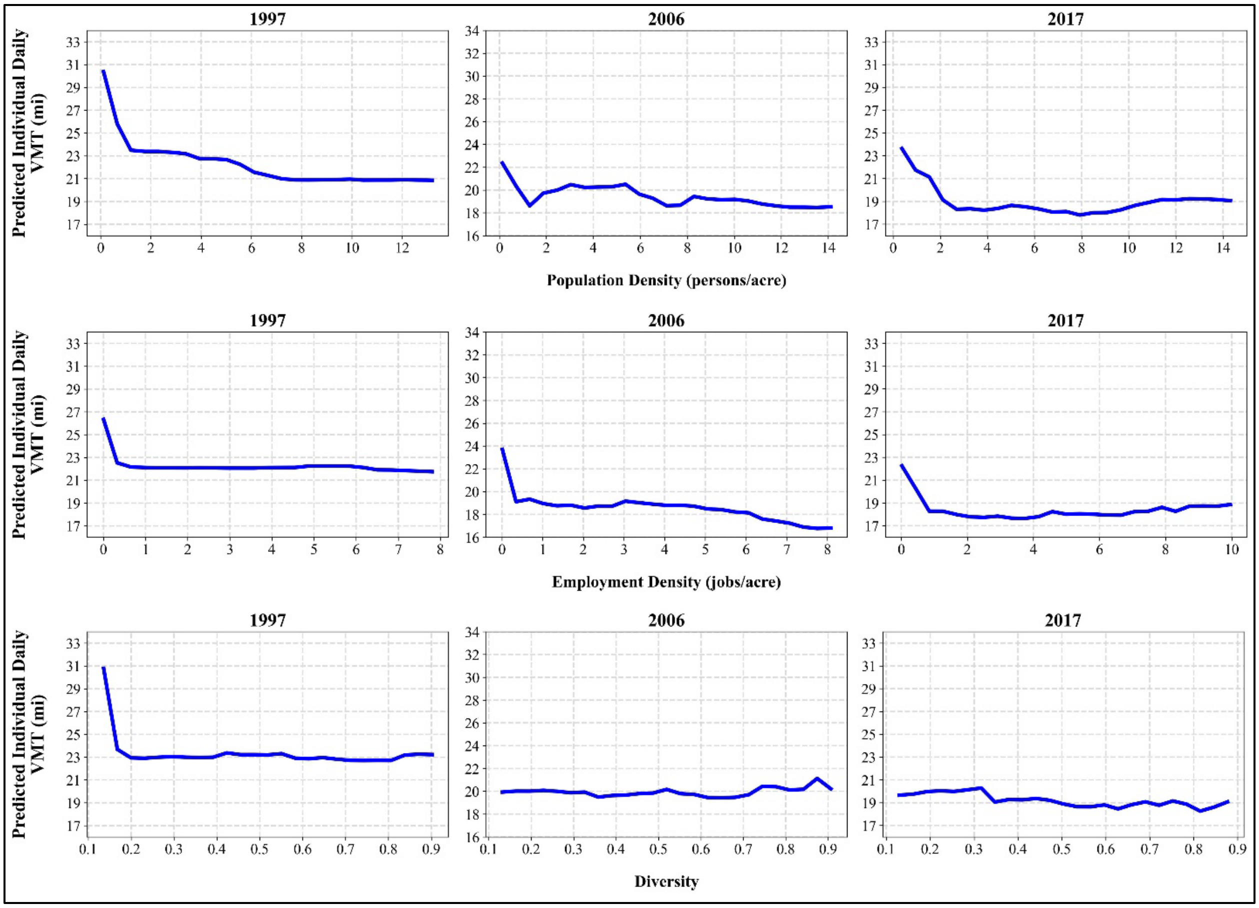

Figure 5: Non-linear Effects of Population Density (PopDEN), Employment Density (EmplyDEN), Diversity (Diversity) on Individual Daily VMT (VMT_Person)

Inferential Modeling

Model Rationale and Specification

Since our dependent variable is continuous, a linear regression model might initially seem appropriate for our study. However, upon examining the structure of our data, we found it to be inherently hierarchical: individuals (*i*) are nested within households (*j*), and households are nested within TAZs (*k*). Due to this clear hierarchical structure, a single-level linear regression model is not ideal, as it assumes independence among observations—an assumption that does not hold in our case. As a result, using a single-level linear regression would lead to inefficient estimates for the study (Sabouri et al., 2020).

In such cases, hierarchical linear regression, also known as multilevel modeling, is the preferred approach. This method overcomes the limitations of traditional linear regression by accounting for the nested structure of the data, allowing for more accurate estimation of coefficients and standard errors (Bryk & Raudenbush, 1992; Sabouri et al., 2020). Consequently, we employed a multilevel modeling approach in our study. Specifically, we allowed only the intercept to vary and keep the slopes constant. Thus, we used a random intercept multilevel modeling technique to simplify model development and interpretation.

For each year's data, we developed a three-level random intercept model. Level 1 captures the effects of personal characteristics, Level 2 addresses household characteristics, and Level 3 incorporates TAZ characteristics. It is important to note that built environment variables such as Dist_transit, Dist_CBD, and Dist_Actvy_Center are associated with individual households and were included at Level 2 of the model for the years 2006 and 2017. However, for the 1997 data, these variables were linked to TAZs because all households within the same TAZ shared the same values. This was due to household locations being approximated by the TAZ centroid, as precise household coordinates were not available. Therefore, these variables were included at the Level 3 for the 1997 model. Other built environment variables, such as PopDEN, EmplyDEN, and Diversity, were TAZ-level characteristics and were included at Level 3 across all three models. The formal specification of the model is as follows:

$$\mathit{Level}\ 1\ \text{(Personal level)}: \quad Y_{ijk} = \beta_{0jk} + \sum_{p=1}^{P} \beta_p X_{pijk} + \epsilon_{ijk}; \qquad \epsilon_{ijk} \sim N(0, \sigma_\epsilon^2)$$

$$\mathit{Level}\ 2\ \text{(Household level)}: \quad \beta_{0jk} = \gamma_{00k} + \sum_{q=1}^{Q} \gamma_q W_{qjk} + u_{0jk}; \qquad u_{0jk} \sim N(0, \sigma_u^2)$$

$$\mathit{Level}\ 3\ \text{(TAZ level)}: \quad \gamma_{00k} = \pi_{000} + \sum_{r=1}^{R} \pi_r Z_{rk} + v_{00k}\,; \qquad v_{00k} \sim N(0, \sigma_v^2)$$

$$\mathit{Combined}: \quad Y_{ijk} = \pi_{000} + \underbrace{\sum_{p=1}^{P} \beta_p X_{pijk}}_{\text{Level 1}} + \underbrace{\sum_{q=1}^{Q} \gamma_q W_{qjk}}_{\text{Level 2}} + \underbrace{\sum_{r=1}^{R} \pi_r Z_{rk}}_{\text{Level 3}} + v_{00k} + u_{0jk} + \epsilon_{ijk}$$

Here, Y_{ijk} is daily VMT for person *i* in household *j* in TAZ *k*. In case of intercepts, β_{0jk} is the household-TAZ-specific intercept varying across households and TAZs; γ_{00k} is the TAZ-specific intercept varying across TAZs; and π_{000} is the global fixed intercept. Additionally, X_{pijk} are Level 1 predictors (e.g., Age, Disability) with coefficients β_p; W_{qjk} are Level 2 predictors (e.g., HH_Size, No_Bike) with coefficients γ_q; and Z_{rk} are Level 3 predictors (e.g., PopDEN, Diversity) with coefficients π_r. Lastly, v_{00k} is the TAZ-level random intercept, u_{0jk} is the household-level random intercept, and ϵ_{ijk} is the individual-level residual error, all independently normally distributed with mean zero and constant variance.

This hierarchical modeling structure not only addresses data dependency but also provides the foundation for incorporating the non-linear and threshold effects identified through our machine learning analysis.

Incorporating Non-Linear Effects into Model

Piecewise regression is a method used to incorporate non-linear effects of numeric variables into regression models (Buscot et al., 2017; Pilgrim, 2021; Toms & Lesperance, 2003). In this study, we used it to model non-linear and threshold effects within multilevel regression models. The knot(s) (breakpoint) for developing piecewise linear segments of a numeric variable were determined based on the findings of PDPs. When selecting the knot(s) for an explanatory variable, we examined the PDPs that depict the relationship between individual daily VMT and the corresponding explanatory variable across all three years. A value of the explanatory variable was identified as a knot if the relationship before and after that point showed visible differences. These knots were then generalized for each explanatory variable based on the results from all three years to avoid issues of overfitting or underfitting. Finally, we constructed piecewise linear segments for the explanatory variables based on these knots.

To incorporate non-linear threshold effects, suppose one key explanatory variable at Level 3, Z, has knots at τ_1 and τ_2. Then, the piecewise components are defined as:

$$Z^{(1)} = \min(Z, \tau_1)\,; \quad \text{if } Z \leq \tau_1$$

$$Z^{(2)} = \max(0, \min(Z - \tau_1, \tau_2 - \tau_1))\,;\ if\ \tau_1 < Z \leq \tau_2$$

$$Z^{(3)} = \max(0, Z - \tau_2)\,; \text{if } Z > \tau_2$$

These segmented variables allow the slope of Z to vary across three ranges: below τ_1, between τ_1 and τ_2, and above τ_2. The multilevel model, incorporating these piecewise terms, becomes:

$$Y_{ijk} = \pi_{000} + \underbrace{\sum_{p=1}^{P} \beta_p X_{pijk}}_{\text{Level 1}} + \underbrace{\sum_{q=1}^{Q} \gamma_q W_{qjk}}_{\text{Level 2}} + \underbrace{\sum_{r=1}^{R} \pi_r Z_{rk}}_{\text{Other Level 3}} + \underbrace{\theta_1 Z^{(1)} + \theta_2 Z^{(2)} + \theta_3 Z^{(3)}}_{\text{Piecewise terms}} + v_{00k} + u_{0jk}$$
$$+ \epsilon_{ijk}$$

Here, Z_{rk} are other Level 3 predictors; $\theta_1, \theta_2, \theta_3$ are the coefficients for the three segments of Z; and all other terms follow the previously defined multilevel structure. This piecewise approach allows flexible modeling of non-linear and threshold effects based on the data-driven breakpoints derived from PDPs in the machine learning step.

Take Dist_CBD as an example. First, we estimated the non-linear relationship between Dist_CBD and VMT_Person using PDPs (**Figure 4**). Upon examining this relationship, we observed that the nature and magnitude of the relationship before and after approximately 5 miles from the CBD differed in the years 1997 and 2017. Additionally, a distinct pattern emerged before and after approximately 15 miles from the CBD, particularly for the year 2006. There might also be another potential breakpoint at 20 miles from the CBD for 2006; however, including this could lead to an overfitting issue. Thus, we identified two knots for this variable: 5 and 15 miles. Using these two knots, we modeled the relationship between Dist_CBD and VMT_Person in three segments within the multilevel model: the first segment reflects the relationship within the 0 to 5 miles range, the second represents the 5 to 15 miles range, and the third represents distances beyond 15 miles.

Here is an example of how to interpret the non-linear results. Consider the Dist_CBD variable for the year 1997 (**Table 3**). Details of the model development process are given in **Section 3.2.3**. Within the 0 to 5 miles range from the CBD, an increase of 1 mile in distance decreases individual daily VMT by 0.69 miles. However, this effect is not statistically significant ($p > 0.1$), indicating that within this range, changes in distance from the CBD do not significantly impact VMT. In contrast, within the 5 to 15 miles range, each additional mile significantly increases VMT by 0.85 miles ($p < 0.01$). Beyond 15 miles from the CBD, each additional mile significantly increases VMT by 1.28 miles ($p < 0.01$).

While numerous inferential modeling techniques—such as polynomial regression, splines, and parametric non-linear models—are available to capture non-linear relationships, we adopted a piecewise linear regression approach due to its methodological rigor, interpretability, and policy relevance. Piecewise regression allows for discrete slope changes at empirically determined thresholds, facilitating the identification of meaningful behavioral shifts that are directly actionable in urban planning contexts. In contrast, other non-linear methods often impose smooth functional forms that can obscure genuine structural changes and complicate interpretation. Moreover, approaches like polynomial regression are susceptible to multicollinearity and overfitting, which compromise the stability of estimates and the reliability of inference. By preserving sharp transitions and avoiding unrealistic curve fitting, piecewise regression provides a more transparent and robust framework for modeling complex, real-world phenomena with practical relevance for policy design.

Model Development Process

The models were developed following a specific step by step procedure. In the first step, we developed a null model. In the second step, we added variables related to individual and household characteristics, including their non-linear effects. In the third step, we incorporated built environment variables without accounting for non-linear effects. Finally, in the fourth step, we included non-linear effects of the built environment factors into the model. At each step, we removed variables that were not statistically significant at the 10% significance level.

Model fit statistics for each step of the modeling process are presented in **Appendix B**. All fit statistics (AIC, BIC, log-likelihood, marginal R^2, and conditional R^2) indicate that the final models for all three years (developed in step 4) are significantly better than the models from the earlier steps. The standard deviations of the random effects at levels 2 and 3 significantly decreased in the models developed in the third step compared to those in the second step. This suggests that incorporating the linear effects of the built environment factors at levels 2 and 3 helps explain a significant portion of the intercept variance at these levels. Furthermore, the standard deviations of the random effects decreased even further in the final models compared to the third-step models, indicating that including non-linear effects of built environment factors can further explain a significant portion of the intercept variance at levels 2 and 3. Overall, these findings demonstrate that models incorporating non-linear effects of the built environment factors are superior, emphasizing the importance of including non-linear effects to improve model performance. The results of the final models are presented in **Table 3**. We also include the results of the models developed in the third step in **Appendix B** to facilitate comparison with the final models.

Elasticity Estimation

To enhance interpretability and inform policy decisions, we estimated the elasticity of the built environment factors after developing the final model (**Table 4**). Elasticity is a unitless metric that quantifies the percentage change in the dependent variable resulting from a one-percent change in an explanatory variable. In the context of piecewise models—where each variable is divided into multiple segments based on empirically derived thresholds—we computed elasticity separately for each segment. The elasticity for the i-th segment was calculated using the following formula, adapted from Ewing and Cervero (2010):

$$\text{Elasticity}^{(i)} = \beta_i \frac{\bar{X}^{(i)}}{\bar{Y}^{(i)}}$$

Where, β_i is the estimated coefficient for the i-th segment of the piecewise variable, $\bar{X}^{(i)}$ is the mean of the explanatory variable within that segment, and $\bar{Y}^{(i)}$ is the mean of the dependent variable for observations within the same segment.

This segment-specific approach enables us to account for non-linearities and threshold effects more precisely, ensuring that each elasticity value reflects the local responsiveness of travel to built environment characteristics. By expressing these effects in relative percentage terms, the elasticities support meaningful comparisons across variables with differing units and scales, and provide actionable insights for policymakers and planners regarding where built environment interventions may be most effective.

Table 3: Result of Multilevel Models

Explanatory Variables	**1997**	**2006**	**2017**
	β (SE)	**β (SE)**	**β (SE)**
Fixed Effects			
Intercept	-11.04 (4.88)**	26.23 (5.27)***	16.33 (3.45)***
Ethnicity [White/Caucasian]	2.26 (1.29) *		
Age [0-6]	3.01 (0.51) ***	-2.13 (0.37) ***	-1.61 (0.26) ***
Age [6-20]	-0.18 (0.19)	0.34 (0.14) ***	0.05 (0.10)
Age [20-50]	0.14 (0.06) **	0.16 (0.05) ***	0.19 (0.03) ***
Age [>50]	-0.18 (0.09) **	-0.32 (0.06) ***	-0.24 (0.04) ***
Disability [Yes]		-3.31 (1.60) **	-2.27 (1.11) **
Licensed_Driver [Yes]	16.10 (1.81) ***	6.94 (1.28) ***	8.33 (0.94) ***
Work_Hr_Wkly			0.06 (0.03) **
Flex_Time [Fixed]	6.88 (1.32) ***	8.85 (1.02) ***	3.26 (1.32) ***
Flex_Time [Flexible]	7.44 (1.32) ***	6.69 (1.16) ***	4.76 (1.23) ***
Home_Office_Wkly [0-3]		0.23 (0.69)	0.55 (0.42)
Home_Office_Wkly [>3]		-3.22 (0.98) ***	-1.93 (0.56) ***
HH_Size [0-6]		-0.80 (0.43) *	
HH_Size [>6]		4.88 (1.58) ***	
No_Employed		-2.67 (0.69) ***	-1.82 (0.44) ***
No_Vehicle [0-2]			1.95 (0.68) ***
No_Vehicle [2-4]			-1.40 (0.58) **
No_Vehicle [>4]			3.32 (2.44)
No_Bike [0-6]		1.10 (0.36) ***	0.52 (0.21) ***

Explanatory Variables	1997	2006	2017
	β (SE)	β (SE)	β (SE)
Fixed Effects			
No_Bike [>6]		-2.61 (3.93)	-2.26 (1.19) *
HH_Selection [Access factor]	-3.53 (1.70) **		-1.64 (0.61) ***
HH_Income [0-20]	-0.04 (0.18)	-0.01 (0.15)	-0.10 (0.14)
HH_Income [20-50]	0.25 (0.07) ***	0.10 (0.05) *	0.10 (0.04) ***
HH_Income [>50]	0.02 (0.03)	0.04 (0.02) ***	-0.02 (0.01) **
Dist_transit [0-7]		1.50 (0.27) ***	1.66 (0.38) ***
Dist_transit [>7]		-0.40 (0.18) **	-5.67 (13.95)
Dist_CBD [0-5]	-0.69 (0.79)		1.26 (0.31) ***
Dist_CBD [5-15]	0.85 (0.27) ***		0.33 (0.11) ***
Dist_CBD [>15]	1.28 (0.20) ***		-0.27 (0.11) ***
Dist_ Actvy_Center [0-2]	3.94 (1.62) **	1.29 (0.92)	
Dist_ Actvy_Center [>2]	-0.18 (0.49)	1.06 (0.26) ***	
PopDEN [0-2]	-6.60 (1.37) ***	-1.14 (1.00)	-2.90 (0.73) ***
PopDEN [>2]	-0.03 (0.19)	-0.22 (0.14) *	-0.01 (0.06)
EmplyDEN [0-1]			-3.76 (0.96) ***
EmplyDEN [>1]			0.01 (0.02)
Diversity [0-0.2]		-39.81 (18.66) **	
Diversity [>0.2]		-1.09 (2.37)	
Random Effects (Standard Deviation)			
Individual (Residual)	23.1	14.8	14.5
Household (Level 2)	17.7	11.2	9.8
TAZ (Level 3)	7.1	0.01	0.6
Sample Size			
Observation	4459	3020	6252
Household	1854	1128	2459
TAZ	485	477	778

***Significant at 1% level, **Significant at 5% level, and * significant at 10% level

Table 4: Elasticity of Built Environment Factors in 1997, 2006, and 2017

Built Environment Factors	1997	2006	2017
Dist_transit [0-7]		0.11***	0.08***
Dist_transit [>7]		-0.19**	-1.32
Dist_CBD [0-5]	-0.13		0.26***
Dist_CBD [5-15]	0.33***		0.16***
Dist_CBD [>15]	0.77***		-0.24***
Dist_ Actvy_Center [0-2]	0.20**	0.09	
Dist_ Actvy_Center [>2]	-0.03	0.21***	
PopDEN [0-2]	-0.13***	-0.03	-0.10***
PopDEN [>2]	-0.01	-0.09*	0.00
EmplyDEN [0-1]			-0.06***
EmplyDEN [>1]			0.00
Diversity [0-0.2]		-0.19**	
Diversity [>0.2]		-0.03	

***Significant at 1% level, **Significant at 5% level, and * significant at 10% level

DISCUSSIONS

Can the built environment sustain as a tool for controlling travel?

Based on the GBDT models, the relative importance of explanatory variables in predicting individual daily VMT was analyzed by estimating feature importance (**Figure 3**). The analysis revealed that built environment characteristics combinedly contributed 50%, 53%, and 54% to the predictive performance of the models in 1997, 2006, and 2017, respectively. This indicates that built environment factors exert a greater influence on the predictive capabilities of the GBDT models than the combined effects of personal and household characteristics. Specifically, the relative importance of individual characteristics was 35%, 29%, and 30% in 1997, 2006, and 2017, respectively, which is consistently higher than the relative importance of household characteristics, which stood at 15%, 18%, and 16% across the same years. This trend demonstrates that built environment characteristics are consistently the most influential and stable predictors of individual daily VMT across all years studied.

This result shows promise for built environment-related policy initiatives aimed at controlling vehicular travel, although some previous studies based on traditional linear models have found that the impact of the built environment on travel is moderate, as suggested by the meta-analysis conducted by Stevens (2017). The relatively strong effect observed in this study could be attributed to two main factors: (a) the study area—Austin—may be a place where people's behavior is more responsive to built environment characteristics; and (b) the flexibility of machine learning methods, which offer advantages over traditional inferential modeling techniques that often struggle to capture non-linear and threshold effects and are limited by multicollinearity, which can distort estimated effect sizes. Recent studies using machine learning techniques and incorporating non-linear relationships have shown similar findings (Chen et al., 2025; Hatami et al., 2023; Liu & Xiao, 2023; Tao & Næss, 2022), suggesting that the built environment has a substantial impact on travel behavior.

Within the built environment characteristics, the distance to the nearest transit stop, the distance to CBD, and the distance to the nearest activity center were the most influential factors in all three years, except for 1997, where the distance to CBD had a moderate effect compared to the other two factors. Population density and employment density also had a moderate impact on VMT in all three years, whereas the diversity index consistently emerged as the least significant factor, particularly in 1997.

In summary, although the relative importance of specific built environment factors fluctuated over the years, the overall influence of built environment characteristics on individual daily VMT remained consistently high and increased marginally over time. These findings underscore the built environment's role as a robust and sustainable tool for mobility management in the long term.

How have the built environment-travel relationship and its magnitude evolved over time?

Distance to nearest transit stop (Dist_transit)

The PDPs reveal that the relationship between the distance to the nearest transit stop and individual daily VMT was positive and nearly linear for the years 1997 and 2017, indicating that as the distance from a transit stop increases, VMT also increases (**Figure 4**). However, in 2006, this relationship was positive and moderately linear only up to a 7-mile threshold, beyond which the distance to the nearest transit stop had no mentionable influence on VMT.

The multilevel models indicate that the distance to the nearest transit stop was not a significant predictor of VMT in 1997 but became significant in both 2006 and 2017 (**Table 3**). Specifically, within the 0 to 7-mile range, greater distances to transit stops were significantly associated with higher VMT in both 2006 and 2017. In this range, an increase of one mile in the distance from the nearest transit stop to a household location led to an increase in individual daily VMT by 1.5 miles in 2006 and 1.66 miles in 2017. However, beyond the 7-mile threshold, the relationship became negative, suggesting that longer distances from transit stops correspond to lower VMT. The impact magnitude was relatively small beyond 7 miles in 2006 and was insignificant in 2017, implying that transit accessibility primarily impacts VMT within a closer range, and its influence diminishes substantially or disappears for those living further out. This counterintuitive reversal beyond the 7-mile threshold may reflect the predominance of rural or peripheral areas with lower overall travel demand—partly due to lifestyle or self-selection effects among residents who travel less—and the diminished relevance of transit access in fully auto-dependent contexts.

Within the 7-mile threshold, the magnitude of impact was greater in 2006 compared to 2017, as indicated by the elasticity statistics. An elasticity of 0.11 in 2006 and 0.08 in 2017 suggests that a 100% decrease in the distance to the nearest transit stop would lead to a 11% and 8% decrease in individual daily VMT, respectively, within this range (**Table 4**). The diminished impact in 2017 may be attributed to the substantial expansion of the transit network during that period, as the average distance to the nearest transit stop significantly declined from 3.56 miles in 2006 to 0.89 miles in 2017 (**Table 1**). This enhanced network coverage may have naturally reduced the marginal benefit of further proximity in reducing VMT in recent years. Nonetheless, since the average distance remains well above the recommended thresholds of 0.25 to 0.5 miles, there is still considerable potential for further VMT reductions through enhanced transit accessibility.

The linear models (Model 3; **Appendix B: Table B2**) yield inconsistent results for distance to transit. While they show significant positive effects in 1997 (0.54) and especially in 2017 (2.17), the 2006 estimate is negative and insignificant (−0.06), which appears counterintuitive. In contrast, the piecewise multilevel models capture consistent and interpretable effects within specific distance ranges, particularly within the 7-mile threshold, offering a more accurate representation of transit accessibility's impact on VMT.

Most previous studies have reported a similar relationship between distance to transit and VMT, which aligns with our findings (Cao et al., 2007; van de Coevering et al., 2021). Through meta-analyses of existing literature, Ewing & Cervero (2010) and Stevens (2017) identified a relatively small elasticity of 0.05 for this variable. In contrast, our study found a substantially higher impact in Austin in 2006 (0.11) and a moderately higher impact in 2017 (0.08) within the 7-mile threshold. This suggests the importance of accounting for threshold effects when estimating the true magnitude of impact, the possibility that transit access has a greater influence in the study area, or a combination of both factors.

In summary, within the 7-mile threshold, the distance to transit is a highly influential factor, particularly in 2006 and 2017, where lower accessibility to transit significantly increases VMT. Additionally, our study uniquely identifies that beyond this threshold, the distance to transit in Austin ceases to be an effective tool for controlling VMT, indicating the presence of a threshold effect.

Distance to CBD (Dist_CBD)

Within the 0 to 5-mile range from the CBD, individual daily VMT showed minimal variation with changes in distance to the CBD for both 1997 and 2006, as indicated by the PDPs (**Figure 4**). However, for 2017, a slight increase in VMT was observed within this range —particularly toward the upper end—as distance from the CBD increased. The results of the multilevel models align with these findings (**Table 3**). The effect of distance to the CBD was not significant for 1997 and 2006, suggesting that within this range, changes in distance had no substantial impact on VMT. However, in 2017, an increase of 1 mile in distance from the CBD to a household significantly increased individual daily VMT by 1.26 miles. The elasticity for this variable in 2017 suggests that doubling the distance to the CBD (a 100% increase) would result in a 26% increase in daily VMT, demonstrating a significant magnitude of influence (**Table 4**).

As indicated by the PDPs, in the 5 to 15-mile range, VMT increased substantially with increasing distance from the CBD in 1997 and very slightly in 2017 (**Figure 4**). However, no clear relationship was found between VMT and distance to the CBD for 2006 within this range. The multilevel models produce results that closely align with the PDPs (**Table 3**). Specifically, an increase of 1 mile in distance from the CBD significantly increased VMT by 0.85 miles in 1997 and by 0.33 miles in 2017. Additionally, the effect was not significant for 2006, indicating that within this range, the distance from the CBD did not influence individual daily VMT in that year. The elasticity values of 0.33 in 1997 and 0.16 in 2017 suggest that doubling the distance within this range would increase individual daily VMT by 33% and 16%, respectively (**Table 4**). These statistics also indicate that the magnitude of impact was twice as high in 1997 compared to 2017.

According to the PDPs, beyond 15 miles from the CBD, a relatively positive linear relationship was found between VMT and distance to the CBD in 1997 (**Figure 4**). However, for 2006 and 2017, this relationship varied slightly without a clear directional trend. The multilevel models also reflect these findings (**Table 3**). Beyond 15 miles from the CBD, an increase of 1 mile in distance significantly increased daily VMT by 1.28 miles in 1997. In contrast, this variable was not significant in 2006. In 2017, although the variable was significant, it had a negative effect on VMT, indicating that for every 1 mile increase in distance from the CBD beyond 15 miles, VMT decreased by 0.27 miles. The elasticity statistics of 0.77 in 1997 and -0.24 in 2017 suggest that doubling the distance within this range would increase VMT by 77% in 1997 and decrease it by 24% in 2017 (**Table 4**).

While the linear models (Model 3; **Appendix B: Table B2**) also show a positive association between distance to the CBD and VMT—with statistically significant coefficients of 0.64 and 0.15 for 1997 and 2017, respectively—it appears to underestimate the effect size. In contrast, the piecewise specification reveals stronger and more localized impacts, particularly within defined distance thresholds. These findings highlight the importance of modeling non-linear relationships to more accurately capture the spatial nuances of how CBD accessibility influences travel behavior.

From the above findings, we can see that the distance from the CBD was one of the most significant factors in controlling VMT in both 1997 and 2017. The results predominantly indicate that the farther from the CBD (signifying lower regional accessibility), the higher the VMT tended to be. This underscores the importance of providing housing opportunities closer to the CBD rather than in peripheral areas to reduce travel. Previous studies have also identified distance from the CBD as a critical factor influencing travel behavior. Meta-analyses by Ewing & Cervero (2010) and Stevens (2017) reported the highest elasticity statistics for this variable in controlling VMT, with values of 0.22 and 0.63, respectively, showing strong consistency with our results.

Interestingly, beyond 15 miles from the CBD, VMT decreased as distance increased in 2017. This decline may be attributed to higher rates of telecommuting and online shopping among residents living more than 15 miles from the CBD in 2017 compared to earlier years, thereby reducing their travel demand. This trend is also reflected in our findings for the variable Home_Office_Wkly [>3], which indicates that individuals working from home three or more days per week tended to have lower VMT in 2017. Notably, this variable was not significant in 1997. Previous studies have similarly shown that individuals residing farther from the CBD are more likely to telecommute and engage in online shopping (Zhu et al., 2023). In summary, residents located at greater distances from the CBD are more likely to substitute physical trips with virtual activities, thereby reducing their overall travel needs.

Distance to the nearest activity center (Dist_ Actvy_Center)

From the PDPs, we observe that within the 0 to 2-mile range from the nearest activity center, VMT increases sharply in 1997 (**Figure 4**). Beyond this threshold, the increase in VMT continues but at a slower, linear rate. In contrast, for 2006 and 2017, within the 2-mile range, distance to the nearest activity center does not appear to significantly influence VMT. However, beyond the 2-mile threshold, a linear positive relationship between VMT and the distance to the nearest activity center becomes evident, particularly for 2006.

The multilevel models confirm these findings, showing that distance to the nearest activity center was significant in 1997 and 2006. Specifically, within the 2-mile range from the nearest activity center, longer distances are associated with higher VMT in 1997, with a notable increase of 3.94 miles in VMT for every additional mile from the activity center. Higher elasticity statistics indicate that a 100% increase in the distance to the nearest activity center results in a 20% increase in individual daily VMT within the 2-mile threshold.

In contrast, in 2006 and 2017, distance to the nearest activity center does not significantly affect VMT within the 2-mile range. Beyond this threshold, longer distances to activity centers positively influence VMT, but significant effects are observed only in 2006. Specifically, in 2006, each additional mile beyond the 2-mile threshold resulted in an increase of 1.06 miles in daily VMT. The elasticity beyond the 2-mile threshold was 0.21 for 2006, indicating that a 100% decrease in the distance to the nearest activity center would reduce VMT by 21%.

Furthermore, the linear specification (Model 3 in **Appendix B: Table B2**) appears to underestimate the magnitude of this effect compared to the non-linear specification, with coefficients of 1.06 in 1997 and 0.89 in 2006. These results underscore the value of incorporating non-linear, threshold-based relationships to more accurately capture the influence of activity center proximity on travel behavior.

In sum, distance to the nearest activity center had a significant influence on individual daily VMT and its impact diminished in 2017. Individuals tend to travel more when living farther from activity centers (low local accessibility). This result is consistent with our expectations and aligns with previous studies (Cao et al., 2007; Zhang & Zhang, 2020).

Population density (PopDEN)

From the PDPs, we observe that population density exhibits a similar kind of relationship with individual daily VMT across all three years (**Figure 5**). VMT decreases significantly with increasing population density up to a threshold of 2 persons per acre, indicating that denser areas up to this point encourage less travel. Beyond this threshold, the impact of population density on VMT weakens.

The multilevel models confirm that population density is statistically significant for all three years, showing a negative relationship with VMT (**Table 3**). Specifically, within the 0 to 2 persons per acre range, increasing population density significantly reduces VMT. For every additional unit increase in population density within this range, VMT decreases by 6.6 miles in 1997, 1.14 miles in 2006, and 2.9 miles in 2017. However, beyond the 2 persons per acre threshold, the effect on VMT is significant only in 2006, with a decrease of 0.03 miles in 1997, 0.22 miles in 2006, and 0.01 miles in 2017 for each additional unit increase in population density.

Elasticity values of -0.13 in 1997, -0.03 in 2006, and -0.1 in 2017 suggest that doubling the population density would result in a 13%, 3%, and 10% decrease in individual daily VMT, respectively, within the 2 persons per acre threshold (**Table 4**). Beyond this threshold, the elasticity values indicate a 1%, 9%, and 0% reduction in VMT in 1997, 2006, and 2017, respectively, due to a doubling of population density, which is less influential compared to the impact within the 2 persons per acre threshold.

Population density exerts a negative influence on VMT across all three years, particularly within the 0 to 2 persons per acre threshold. This result aligns with expectations and is consistent with previous research suggesting that higher population density can reduce VMT. However, meta-analyses by Ewing & Cervero (2010) reported relatively low elasticity values for this variable, with an estimated elasticity of 0.04, while Stevens (2017) estimated a range between −0.10 and 0.22 —to some extent similar to our study. Additionally, a study by Zhang & Zhang (2020) reported an elasticity of 0.026 for population density in Austin, which is notably lower than our estimates within the 2 persons per acre threshold.

The lower estimates may arise from the lack of consideration of threshold effects in previous studies, which potentially undermined the policy relevance of population density. Further support for this interpretation is evident from the linear multilevel model results (Model 3; **Appendix B: Table B2**), where the estimated coefficients for population density were −0.38 in 1997, −0.40 in 2006, and −0.15 in 2017. These estimates are markedly lower than those produced by the piecewise model, highlighting the importance of capturing non-linear effects.

Our study, however, clearly demonstrates that within the 2 persons per acre threshold, population density significantly impacts VMT and, therefore, has considerable policy relevance. To provide additional context and emphasize this point, it is important to note that, in 2017, 51% of the TAZs had a population density below this threshold.

Employment density (EmplyDEN)

From the PDPs, we can observe that individual daily VMT decreases with an increase in employment density up to a threshold of 1 job per acre in all three years (**Figure 5**). Beyond this threshold, employment density appears to have no influence on VMT in 1997 and 2017, while a slightly negative relationship is observed in 2006.

When comparing results from the multilevel models, the effect of employment density is not statistically significant in 1997 and 2006 (**Table 3**). However, it becomes statistically significant in 2017, suggesting that its influence may have emerged over time. Within the 1 job per acre threshold, a one-unit increase in employment density decreases individual daily VMT by 3.76 miles, indicating that living in areas with more job opportunities nearby reduces travel. The elasticity statistic is -0.06, meaning that doubling the number of jobs within this threshold decreases VMT by 6% (**Table 4**). Beyond this range, however, employment density does not have any significant influence. It is worthy to mention that, in the linear models (Model 3; **Appendix B: Table B2**), this variable is insignificant in all years, highlighting the importance of incorporating non-linear effects to uncover the true magnitude of the relationships.

In previous studies, Ewing & Cervero (2010) and Stevens (2017) also reported low elasticity values for employment density in relation to VMT reduction, with estimates of 0.0 and 0.07, respectively. These figures indicate a relatively comparable impact to our findings within the 1 job per acre threshold in 2017. Our results underscore that employment density within this threshold is relevant for policy considerations and may yield high marginal impacts in the future, as this variable is only now emerging as a significant factor. To further contextualize this, it is noteworthy that, in 2017, 55% of the TAZs had a job density below this level.

Diversity

From the PDPs, it is evident that diversity generally does not influence individual daily VMT, except within the 0 to 0.2 entropy index range for the year 1997 (**Figure 5**). Within this threshold, increasing diversity substantially decreases VMT.

The multilevel models show that diversity was not significant in 1997 and 2017 but was significant in 2006, suggesting that its impact emerged in 2006 and then diminished afterward (**Table 3**). Specifically, within the 0.2 diversity threshold in 2006, a 0.1 unit increase in diversity entropy reduces VMT by 3.98 miles. The linear model underestimates this effect, showing that a 0.1-unit increase reduces VMT by only 0.4 miles (Model 3; **Appendix B: Table B2**). The elasticity value of -0.19 indicates that doubling diversity within this range could reduce VMT by 19% (**Table 4)**. Beyond this threshold, diversity does not have a significant effect on VMT.

In summary, diversity appears to be a relatively less influential factor in the study area overall, with limited potential for large-scale impact given that the average diversity index across TAZs is already 0.56. However, increasing diversity can still contribute to VMT reduction in TAZs with low diversity—particularly those with an entropy index below 0.2—underscoring the potential of mixed-use environments to promote shorter travel distances and fewer trips. When comparing these results with previous ones, while Ewing & Cervero (2010) and Stevens (2017) reported very small and counterproductive elasticity values, Zhang & Zhang (2015) estimated an elasticity value of 0.2 for Austin, which is comparable with our study.

CONCLUSIONS AND IMPLICATIONS

Summary and Practical Relevance of the Study

This study examines the dynamic relationship between the built environment and travel behavior, specifically individual daily VMT, over a 20-year period in Austin, Texas. Utilizing three waves of household travel survey data from 1997, 2006, and 2017, it integrates the strengths of machine learning and inferential modeling to introduce a novel approach for accurately and efficiently understanding the non-linear and threshold effects of the built environment on travel behavior.

Through a repeated cross-sectional approach, this study reveals that built environment factors consistently account for 50% or more of the relative importance in predicting individual daily VMT, exerting a greater influence than personal and household characteristics combined across all three years. This finding underscores the built environment's long term potential as a tool for managing travel. Notably, it provides robust evidence of the enduring effectiveness of built environment factors on travel behavior—an assumption often made by researchers but rarely supported by empirical evidence.

The study further contributes to the field by identifying key non-linear relationships and threshold effects that are critical for policymaking. Among the built environment factors, distance to the nearest transit stop emerged as a dominant predictor of VMT, especially in 2006 and 2017. For distances within a 7-mile threshold, increased transit accessibility was associated with reduced daily VMT; beyond this threshold, transit accessibility had no significant effect. However, due to Austin's extensive transit network expansion after 2005, the influence of this variable was slightly less pronounced in 2017 compared to 2006.

Regional and local destination accessibility was also critical. Both the distance to the CBD (regional accessibility) and the nearest activity centers (local accessibility) were more influential in 1997 than in later years. In 2006, local accessibility became more important, while regional accessibility gained significance in 2017. Lower regional accessibility generally led to higher VMT, except in 2017, when greater distances beyond the 15-mile threshold were associated with reduced VMT—possibly due to the rise of virtual activities. Local accessibility had a significant impact in both 1997 and 2006, suggesting that greater local accessibility helps reduce VMT. However, the effect sizes of destination accessibility factors appear to have diminished over time.

Population density consistently impacted VMT across all years, with a notable reduction observed up to a threshold of 2 persons per acre. The similarity in effect sizes across the three years highlights that there is still room for further improvement. Similarly, employment density emerged as influential in 2017, reducing VMT within a threshold of 1 job per acre. Diversity, while less influential overall, significantly reduced VMT—only in 2006—up to an entropy index of 0.2.

The results confirm prior hypotheses while providing more nuanced evidence regarding the magnitude and nature of the relationships between the built environment and travel behavior through the identification of non-linear effects and thresholds. Policy implications include promoting smart growth strategies such as enhancing transit accessibility in areas where the average distance to transit falls within the 7-mile threshold; encouraging population and employment densification, particularly up to 2 persons per acre and 1 job per acre, respectively; and discouraging single-use development by targeting a mixed-use entropy index of at least 0.2. Additionally, preventing sprawl by concentrating development within 5 miles of the CBD and 2 miles of local activity centers is critical. As the dynamic results show that destination accessibility factors have become less influential in recent years and diversity has approached its optimal impact level, greater emphasis should be placed on improving transit accessibility, population density, and employment density. These factors hold untapped potential and could become key drivers in reducing car dependency in Austin in the coming decades.

Theoretical implications

This study offers significant theoretical contributions by proposing a fresh perspective in the existing literature that often implicitly assumes the effects of the built environment variables on travel behavior are static and uniform over time. Our research empirically demonstrates that the magnitude and, in some instances, even the direction of these impacts are inherently dynamic and context-dependent, varying across distinct temporal contexts and spatial thresholds.

A central theoretical contribution lies in the explicit identification and empirical validation of threshold effects. The findings reveal that the influence of built environment factors on VMT is not consistent across all ranges; rather, these effects diminish substantially—and in some cases become negligible—beyond certain critical thresholds. Furthermore, the study introduces the concept of diminishing marginal returns within built environment interventions: the marginal impact on VMT tends to be more pronounced when a built environment characteristic's value lies at the lower end of its respective thresholds, whereas its impact weakens as values approach higher saturation levels.

These insights are rigorously grounded in observed patterns across the study's multi-year dataset. For instance, local and regional accessibility were strong determinants of VMT in earlier years, but their influence has distinctly declined in more recent years, likely due to the growing frequency of virtual activities such as telecommuting and online shopping. In contrast, factors such as transit accessibility and diversity have gained prominence more recently but now exhibit signs of diminishing returns—particularly in the case of diversity, which appears to have reached a saturation point in the study area. Looking ahead, population and employment density—still below critical thresholds in a substantial share of the study area—offer considerable potential for future impact, along with transit access, which remains effective despite a declining marginal effect.

Finally, this study demonstrates that while the relative importance of individual built environment variables may fluctuate over time, the overall influence of the built environment on travel behavior remains consistently high. This suggests that strategic enhancements to underperforming built environment characteristics can serve as a sustainable and adaptive tool for managing travel demand in the long term. By advancing the understanding of temporal dynamics, threshold effects, and marginal returns, this study contributes a novel theoretical framework for future research and policy development in the domain of built environment–travel behavior interactions.

Methodological implications

While machine learning and inferential modeling have traditionally been applied separately in travel behavior research, our study introduces a novel integration of the two. Rather than using machine learning solely for prediction, we employ it as a diagnostic tool to uncover complex non-linear relationships and inform the specification of interpretable statistical models. This data-driven exploration of non-linear structures helps overcome the assumption-driven, trial-and-error approach commonly used in inferential modeling, which is often prone to bias and inaccuracy. By leveraging PDPs from GBDT models to identify optimal threshold points, we guide the piecewise specification within a multilevel regression framework. In doing so, we address key limitations of machine learning methods—namely, their lack of statistical inference and limited interpretability. This integrative approach not only captures complex non-linearities but also enhances interpretability, reduces researcher bias, and enables valid statistical inference, ultimately yielding more robust and policy-relevant insights.

Nevertheless, we acknowledge several limitations and opportunities for improvement in future studies. While PDPs enhance interpretability, they still involve subjective judgment in determining the optimal number and location of thresholds, which may introduce research bias—albeit to a very limited extent. Future research should explore methods to further reduce such bias. Additionally, PDPs can yield inaccurate results due to unrealistic feature combinations, particularly in the presence of strong multicollinearity. Although this was not a major issue in our dataset, researchers should exercise caution and consider alternative XML techniques, such as ALE plots and SHAP values, when appropriate.

Beyond these concerns, future research could extend our framework by testing it across different urban contexts to validate the thresholds and nonlinear effects observed, thereby enhancing generalizability. Additionally, incorporating cohort-based pseudo-panel approaches using repeated cross-sectional data may also help in examining causal relationships more robustly. Finally, our analysis does not account for interaction effects among independent variables. A promising direction for future work would be to adopt a similar approach to ours—using XML methods to identify relevant interaction effects in the data and incorporating them into inferential models to enhance statistical inference and interpretability.

APPENDIX A

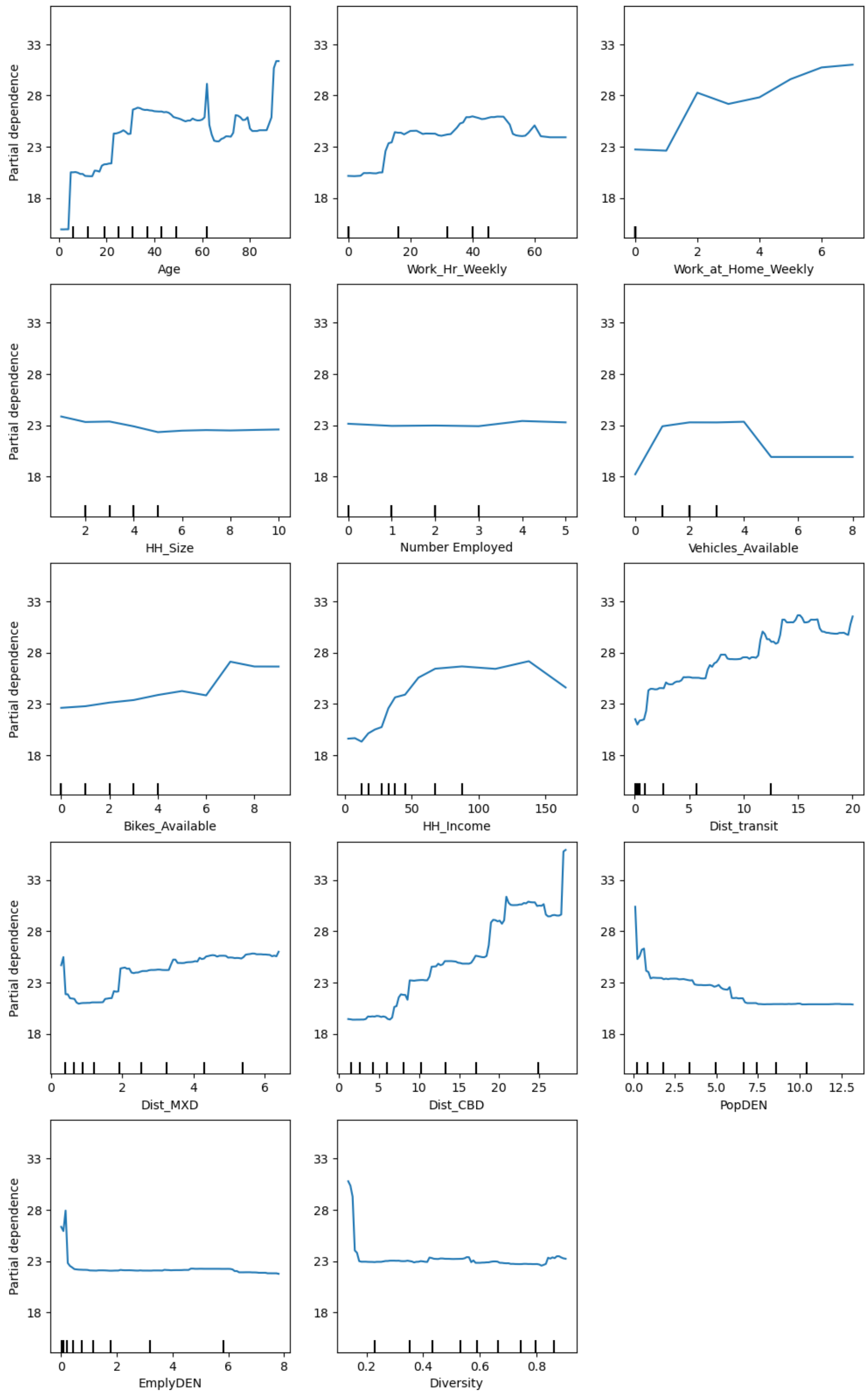

Figure A1: Relationship between VMT_Person and numeric explanatory variables in 1997

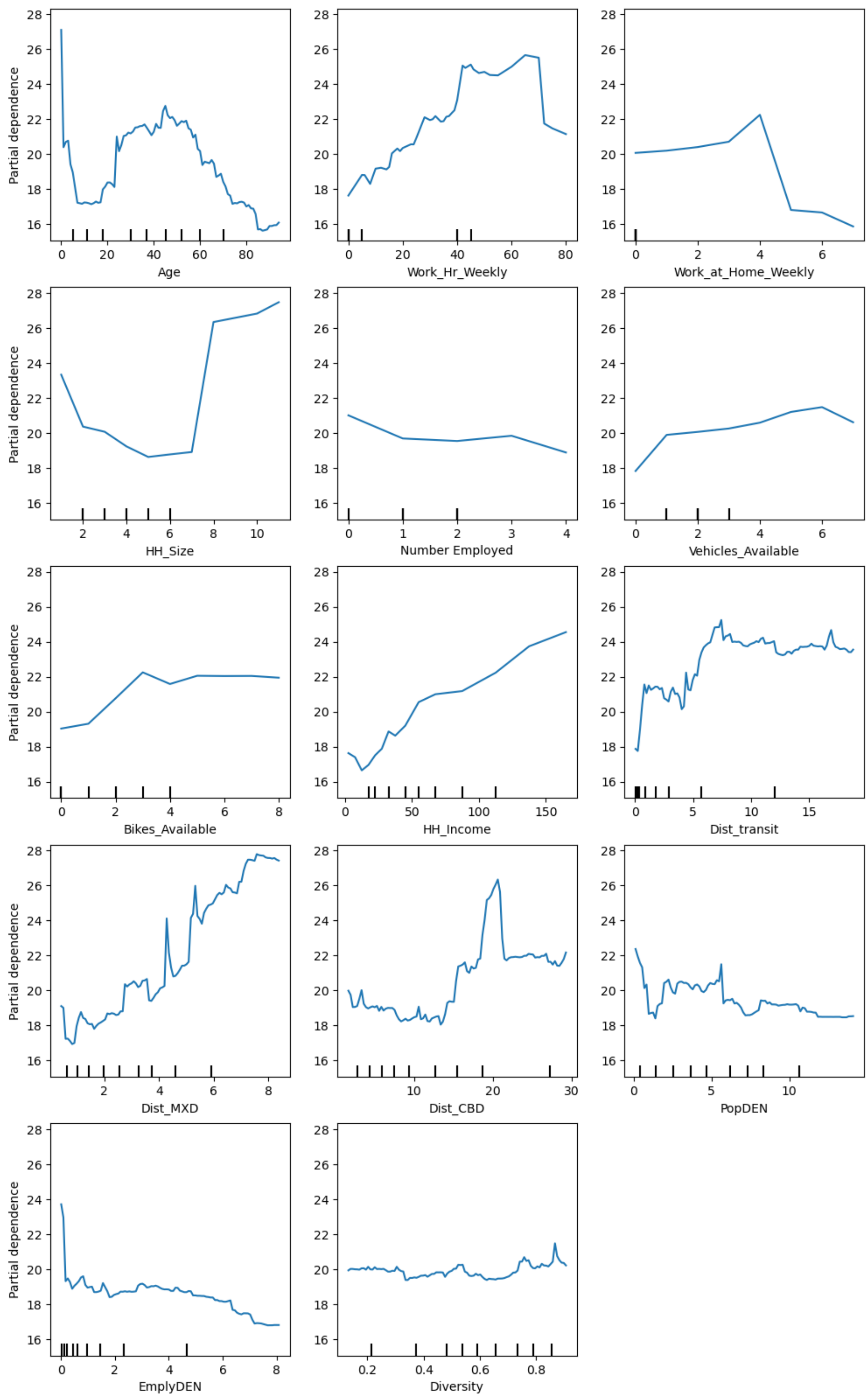

Figure A2: Relationship between VMT_Person and numeric explanatory variables in 2006

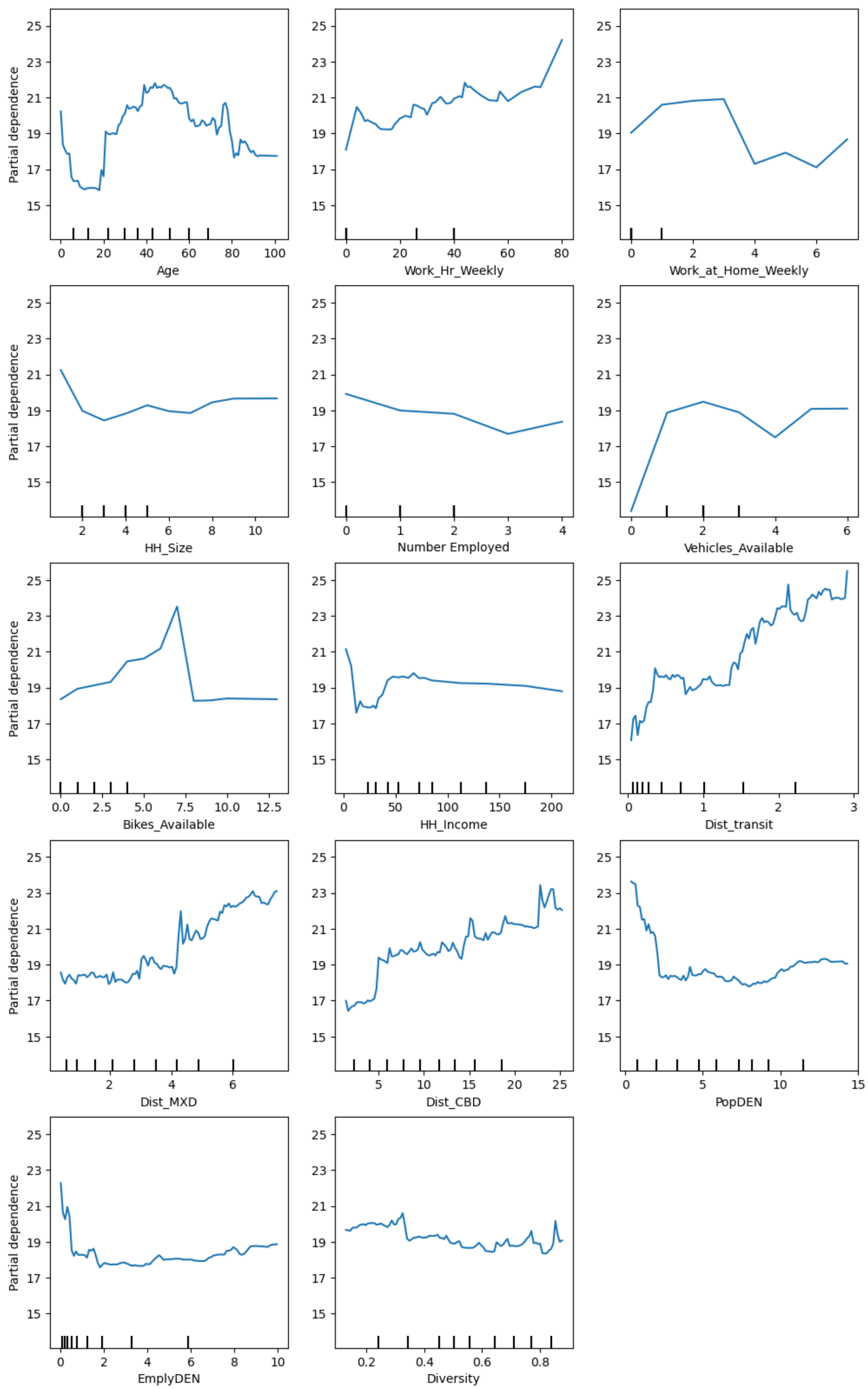

Figure A3: Relationship between VMT_Person and numeric explanatory variables in 2017

APPENDIX B

Table B1: Fit statistics of the multilevel models

Model for 1997				
Criteria	**Model 1[1]**	**Model 2[2]**	**Model 3[3]**	**Model 4[4]**
AIC	43325.2	42562.1	42381.1	42364.6
BIC	43350.8	42690.1	42547.4	42511.7
logLik	-21658.6	-21261.1	-21164.5	-21159.3
Marginal R^2	0.00	0.14	0.24	0.25
Conditional R^2	0.42	0.55	0.55	0.55
Individual (Residual)	26.07	23.11	23.09	23.10
Household (Level 2)	16.89	17.55	17.59	17.69
TAZ (Level 3)	14.31	13.86	8.13	7.10
Model for 2006				
AIC	26673.9	26020.2	25890.1	25857.0
BIC	26697.9	26170.3	26076.2	26037.2
logLik	-13333.0	-12985.1	-12914.1	-12898.5
Marginal R^2	0.00	0.19	0.26	0.27
Conditional R^2	0.37	0.54	0.54	0.54
Individual (Residual)	16.95	14.74	14.75	14.75
Household (Level 2)	11.72	12.16	11.36	11.22
TAZ (Level 3)	5.82	3.76	0.00	0.00
Model for 2017				
AIC	54399.9	53299.5	53090.6	53049.2
BIC	54426.9	53481.4	53312.9	53278.2
logLik	-27196.0	-26622.8	-26512.3	-26490.6
Marginal R^2	0.00	0.14	0.20	0.21
Conditional R^2	0.27	0.46	0.46	0.46
Individual (Residual)	16.59	14.51	14.49	14.48
Household (Level 2)	8.86	9.81	9.85	9.78
TAZ (Level 3)	4.97	5.00	1.18	0.63

[1]Model 1: Null Model

[2]Model 2: Model with individual (Level 1) and household (Level 2) characteristics as predictors, without any built environment-related predictors

[3]Model 3: Model 2 with the addition of all built environment-related predictors, without considering their non-linear effects

[4]Model 4: Model 2 with the addition of all built environment-related predictors, including their non-linear effects

Table B2: Results related to built environment factors (not full model) in Model 3

Built environment Variables	1997	2006	2017
	β (SE)	**β (SE)**	**β (SE)**
Dist_transit	0.54 (0.28)**	-0.06 (0.16)	2.17 (0.34)***
Dist_ Actvy_Center	1.06 (0.39)***	0.89 (0.21)***	0.80 (0.16)***
Dist_CBD	0.64 (0.22)***	0.34 (0.12)***	0.15 (0.05)***
PopDEN	-0.38 (0.17)**	-0.40 (0.13)***	-0.15 (0.05)**
EmplyDEN	0.00 (0.08)	-0.08 (0.10)	0.00 (0.02)
Diversity	-7.65 (3.12)***	-4.24 (2.07)**	-3.15 (1.31)**

***Significant at 1% level, **Significant at 5% level, and * significant at 10% level

Table B2 presents the linear relationships between built environment factors and individual daily VMT as estimated in Model 3. Several of these linear relationships are statistically significant in this model but become insignificant in Model 4, where non-linear (piecewise) specifications are introduced. To further examine this, we tested whether reintroducing the linear forms of these variables—while maintaining non-linear specifications for the others—would restore their significance in Model 4. In all such cases, the variables remained insignificant.

Given the low correlations among built environment variables in our dataset, and considering that all model fit indices favor Model 4, we interpret the linear specifications in Model 3 as likely misspecified. The significance observed in the linear model may reflect spurious or overstated effects due to omitted non-linearities in other variables. Once piecewise functional forms were used to better capture threshold effects, these apparent relationships disappeared—regardless of whether the tested variable was included linearly or non-linearly—underscoring the importance of using flexible functional forms to uncover the true nature of built environment–travel behavior relationships.

For instance, in the 1997 data, Dist_transit appeared significant in the linear Model 3 but became insignificant in both segments once modeled using a piecewise specification in Model 4. We further tested an extended version of Model 4, reverting Dist_transit to a linear form while keeping non-linear specifications for other variables. Yet again, Dist_transit remained insignificant. This suggests that in the initial linear model, Dist_transit may have been capturing variation that more appropriately belonged to Dist_CBD and PopDEN, whose effects were misrepresented under linear assumptions. Once those effects were properly modeled, Dist_transit no longer contributed meaningfully to the explanation of VMT.

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