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ORIGINAL ARTICLE SCIENCE & ENGINEERING

INFLUENCE OF URBAN FORM CHARACTERISTICS ON TRAVEL BEHAVIOR: EVIDENCE FROM AUSTIN, TEXAS

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Abstract
Understanding the relationship between the physical form of the built environment and how people travel from origin to destination is vital to formulate policies to reduce the distance traveled and promote public transit. This study has used Austin activity-travel survey data to explore the influence of urban form characteristics on travel behavior. It has been hypothesized that mixed-use high-density development significantly impacts people's travel behavior in this area. Urban form variables like increase in density, better street connectivity, and mixed land use TAZ as origin and destination have been found to be significant in reducing the distance traveled and car dependency. Even after controlling the trip makers' and alternative specific characteristics, urban built form is showing a clear and strong impact on mode choice behavior. Though personal characteristics remain important after including the built form variables, built form variables also show significant influence on mode choice behavior. The results support the hypothesis of this study that mixed-use high-density development has a significant impact on the mode choice behavior of the people of the Austin area. These findings suggest that transportation policy formulation is not only an economic decision but also a land use planning decision. City authorities aiming to reduce automobile trips and distance travelled need to consider these built form characteristics to determine suitable areas to invest to yield the highest return in promoting transit use and active transportation.

Keywords: Built environment, land use, mode choice, discrete choice, mixed land use, transit

Introduction

Although there is a significant amount of literature on investigating the relationship between the physical form of the built environment and the way people travel from origin to destination, the varied nature of empirical findings does not allow to reach consensus. Despite some ambiguous findings, many studies have suggested that the transformation of urban form into a more compact, mixed-use, and transit-friendly pattern will reduce car dependency and increase transit use and active transportation (Ewing & Cervero, 2010; Zahabi et al., 2015; Nasri & Zhang, 2019). While researchers including Ewing & Cervero (2010) claimed that compact urban forms have significant influence on driving less, other researchers including Stevens (2017) concluded that compact development does not have much influence on driving less.

To explain the built form characteristics, researchers have used several variables commonly known as 'D' variables. The original three 'D's were density, diversity, and design to quantify built form (Cervero & Kockelman, 1997). Later, researchers have used 5Ds – adding destination accessibility and distance to transit to the previous list. (Ewing & Cervero, 2001; Ewing et al., 2009). Some recent studies have used 6Ds by adding demand management, including parking supply and cost (Ewing & Cervero, 2010), and 7Ds by adding Demographics to quantify the built environment (Ewing & Cervero, 2010).

'Density' variables have been measured as the density of population, dwelling units, employment, building floor area, or something else. Some studies have used activity density, a combined density of population and employment (Dunphy & Fisher 1996, Cervero & Kockelman 1997; Zegras 2010). Several studies have found that high (residential) density areas promote higher transit usage and less driving (Dunphy & Fisher, 1996; Cervero & Kockelman, 1997). Studies have found that higher walkability and street connectivity result in less auto travel and higher non-motorized trips (Cervero & Kockelman, 1997). Most of these studies have been conducted using census blocks, tracts, and traffic analysis zones (TAZ) as geographical units (Dunphy & Fisher 1996, Cervero & Kockelman

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1997; Ewing et al. 2009). The reason is understandable because data about urban built forms are mostly available for these resolutions. Several studies (Zegras, 2010; Boarnet & Crane, 2001) have found that estimating the relationship between urban form and travel behavior produces different results for different geographic levels. Studies have suggested that active transportation is highly influenced by built forms of local neighborhoods, whereas the choice of the automobile depends more on regional land-use patterns (Ardeshiri & Vij, 2017).

Diversity has been measured as the number of different land uses in a single region. Some studies (Cervero & Kockelman, 1997; Kitamura et al., 1997) have used Entropy to measure diversity: low for single-use environments and higher for multiple land-use areas. Diversity has an impact on accessibility to destination and land-use balance. Several studies have found the relationship is statistically significant that higher diversity reduces the number of trips and trips by automobiles (Cervero, 1996; Cervero & Kockelman, 1997; Kitamura et al., 1997; Kockelman, 1997; Ewing and Cervero, 2010). Kockelman (1997) has used land use-accessibility balance, and household and travelers characteristics to predict travel behavior.

Design is mostly measured by street network characteristics. Dense urban grids of high interconnectivity, straight or curving streets forming loops, and 'cul-de-sacs' in the suburban or less-density areas – are some measures of design characteristics. These also include average block size, the proportion of four-way intersections, and a number of intersections per square mile. Studies have found that high-density grid iron street design, along with fewer parking opportunities lead to less VMT and increase of transit use (Kitamura et al., 1997; Kockelman, 1997; Ewing and Cervero, 2010). Neighborhoods with pedestrian-oriented design, better street connectivity, transit-oriented mixed-use development, and high population density promote switching to active transportation or transit and reduce driving (Cervero, 1996; Kitamura et al., 1997; Frank et al. 2000).

Several studies argued that while any single 'D' variable may not have a significant impact in a particular case, the combined effect of the Ds is substantial on travel behavior (Ardeshiri & Vij, 2017). The majority of the research on this topic has taken the micro approach and considered the land use and built form characteristics only at the local and neighborhood level, such as density, land use mix, street connectivity, transit accessibility etc. (Ewing & Cervero, 2010). This approach suffers from not considering the impact of large-scale land-use patterns and the overall spatial pattern of the city and the region, which also significantly influences travel behavior (Nasri & Zhang, 2012). Improved mobility of modern time has encouraged people to make trips connecting land uses on a large scale. Thus activity space has grown bigger, connecting their home and work along their commuting routes. This makes it important to consider macro-level built environment characteristics to study travel behavior rather than confining it to just immediate neighborhood. Though a limited number of studies have investigated the impact of the built environment at the city and regional level on travel behavior, they have found that macro variables are at least equally influential in determining travel behavior (Boarnet & Sarmiento, 1998). Due to advancements in the transport sector, people are no longer confined to their own neighborhoods or cities. They can travel further distances connecting large geographical spaces for employment, shopping, or entertainment opportunities (Nasri & Zhang, 2019). The physical form of cities, population and employment density, settlement size and pattern, Land use, transportation infrastructures, job-housing balance, degree of decentralization or concentration, etc. have a significant impact on housing and transportation decision (Newman & Kenworthy, 1999; Yang & Ferreira, 2008).

Few studies have introduced the sprawling nature of urban areas to define metropolitan level built form in travel behavior studies (Ewing et al., 2002; McCann & Ewing, 2003). To quantify urban sprawl, most of these studies used density and changes of density over time. In an earlier study, Kain and Fauth (1976) investigated the impact of urban form on travel behavior in 125 metropolitan areas. Their study's metropolitan level variables include employment opportunities at CBD, the density of the central city, percentage of single-family dwelling units, supply of transport infrastructures, and composition of workplaces.

One important consideration in studying the causal relationship between urban form and mode choice behavior is the 'residential self-selection' effect (Nasri, 2016). It has been argued that the choice of transit or active transportation might not be the direct result of characteristics of built environment rather it might be the lifestyle orientation of the individual which leads the individual to choose a high density, transit and pedestrian friendly neighborhood. If this effect of 'self-selection' of neighborhoods is very large and not controlled in a statistical model the output will be biased in favor of urban form characteristics. Researchers have tried to quantify this 'self-selection' effect by using many different approaches. Majority of the studies have included variables explaining personal attitudes in the model to control the 'self-selection' effect (Kitamura et al., 1997; Cao et al., 2007; Ewing & Cervero, 2010). These studies have found this effect significant in determining travel behavior and some studies suggested that 'self-selection' has equal or even stronger impact on travel behavior than true impact of land-uses

(Cao et al., 2007). Researchers have argued that long term decisions like residential location choice and car ownership do not depend on short run mobility decision rather depends on long term lifestyle decisions (Boarnet & Crane, 2001; Walker & Li, 2007).

To address the impact of 'self-selection' some studies have included socio-economic factors which are correlated to travel behavior in the model ((Brownstone &Golob, 2009), some have included factors that determine travel attitudes (Kitamura et al., 1997), some have used structural model to capture the two-way impacts (Vance &Hedel, 2007), and some have used longitudinal analysis to capture the behavioral changes regarding travel behavior (Cao et al., 2009).

Since the varied nature of empirical findings does not allow to reach consensus, this study attempted to investigate the debate by exploring the influence of urban form characteristics on travel behavior in the Austin area. It has been hypothesized that mixed-use high-density development has a significant impact on people's travel behavior in this area. Two kinds of relationships- the relationship between built forms and distance traveled and the relationship between built forms and mode choice behavior- have been investigated using ordinary least squares regression (OLS) and multinomial logit model (MNL), respectively.

Materials and Methods

To explore the influence of urban form characteristics this study has investigated the impact on both distance travelled and mode choice behavior of the people at Austin. Ordinary least squares regression (OLS) has been used to investigate the relationship between built forms and distance travelled. To investigate the mode choice behavior multinomial logit model (MNL) has been developed to capture the discrete choice behavior of the people. All the variables used in these models have been processed using transCAD software. Both the OLS model and MNL model have been developed in 'R' platform.

Data Processing

The variables for both the OLS model for distance travelled the and MNL model for mode choice behavior have been derived from raw Austin activity travel survey 2017-2018 data and Austin TAZ 2015 GIS data using transCAD. Alternative specific variables cost and time for each mode have been processed through network analysis function in transCAD. TransCAD has been used to create network for Car, Bus, Bicycle and Walk modes and skim matrices for all the four modes have been generated. TransCAD has also been used for several data wrangling functionalities such as joining several data files (household information, person information, trip information) of Austin activity travel surveys to get the required variables, making queries (selection by condition etc.) and data transformation (group by etc.). Several tools (tag, overlay etc.) for geographic analysis in transCAD have been used to process GIS data (population density, employment density etc.) to get required variables. For example, 'Intersection density for each TAZ' variable have been processed using the 'from node-to node' information using GIS functionalities of TransCAD.

Discrete Choice Modeling to Study Impact of Urban Form on Mode Choice Behavior

It needs to be noted that most of the studies on this topic have only confirmed the association of urban form with travel behavior; few have tried to investigate the casual relationship between these two. Majority of these studies who looked into causal relationship have used discrete choice modelling to investigate the causal relationship between urban form and mode choice beahvior (Cervero & Kockelman, 1997; Frank et al., 2000; Nasri & Zhang, 2019). These studies have confirmed that impact of urban form on travel behavior is practically and statistically significant (Cervero and Kockelman, 1997; Cao et al., 2007; Ewing & Cervero, 2010). Limited number of studies have attempted to capture the spatial autocorrelation effect of the urban form and socio-economic characteristics to explain the mode choice behavior (Nasri, 2016).

This study used Multinomial Logit model to establish the basis for discrete choice framework and using the random utility model as decision rule will calculate the probability of selecting a particular mode evaluating its utility against the utility of all other available alternatives. In a discrete choice framework, an individual first see the available alternative modes, then evaluate different attributes of those alternatives under some given criteria (led by his socio-economic characteristics) and use a decision rule to select most suitable alternative for him from the available modes (Koppelman & Bhat, 2006). An individual always try to maximize his/her utility when selecting the mode for his trips. Trip maker evaluate the derived the utilities of the modes from attributes like trip cost, trip time, safety, comfort, etc. and choose the mode with highest utility (Ben-Akiva & Lerman, 1994). This is called utility maximization when making choices.

A utility function of a mode "m" can be expressed mathematically as,

$$U_{mi} = \beta_1 X_{mi1} + \beta_2 X_{mi2} + \ldots\ldots\ldots\ldots\ldots + \beta_k X_{mik} \qquad (2.1)$$

Where,
U_{mi} is the net utility function for a mode 'm' for individual i;
X_{mi1} , …, X_{mik} are k number of attributes of a mode m for individual i; and
β_1 , ………, β_k are k number of coefficients (or weights attached to each attribute) which need to be inferred from the survey data.

Thus a utility function of a specific mode is a linear combination of various explanatory variables along with an alternative specific constant term which reflects relative preference for that alternatives. In a three mode hypothetical situation where bus transit, auto and train compete each other, utility functions of the modes can be written as,

Utility bus = ASC bus + (β1* IVTT bus) + (β2 * OVTT bus) + (β3* Cost bus) +…………(1)
Utility auto = ASC auto + (β1* IVTT auto) + (β2 * OVTT auto) + (β3* Cost auto) +…….(2)
Utility train = ASC train + (β1* IVTT train) + (β2 * OVTT train) + (β3* Cost train) +…....(3)
Where,
IVTT = In-Vehicle Travel Time
OVTT = Out-of-Vehicle Travel Time

In this situation,the multinomial logit model establishes the basis for the discrete choice framework, and using random utility model as a decision rule calculates the probability of selecting a particular mode by evaluating its utility against the utility of all other available alternatives. This can be expressed mathematically as,

$$P_i = \frac{e^{U_i}}{\sum_{j=1}^{j} e^{U_j}}$$

Where,
i and *j* are alternatives in a choice set,
P_i is the probability of choosing Mode *i*,
J is the set of all alternatives available to the individual (including modes *i* and *j*),
U is the utility associated with a given mode
For example, using the three mode example illustrated above the probability of using bus over other modes can be calculated as,

$$P_{bus} = \frac{e^{U_{bus}}}{e^{U_{bus}} + e^{U_{auto}} + e^{U_{train}}}$$

Factors affecting mode choice in a discrete choice framework

McFadden (1978) had studied the factors influencing the choice of mode in a discrete choice framework and they are variables with critical explanatory power - travel cost, on vehicle time, walk time, transfer wait time, transit initial headway, and number of persons in household; variables with important explanatory power - numbers of transfers, respondent's relation to household head, employment density at work location, suburban or urban, family composition; variables with ambiguous explanatory power - household income, residential population density, CBD location with respect to residence, number of workers in household, age of household head, reliability of transportation mode, perception of comfort, safety, convenience; variables with low explanatory power- CBD work location, sex of respondent, age of respondent, work status of household head, general attitudes toward privacy, and delay. Papacostas & Prevedouros (2015) had categorized the variables related to mode choice behavior of trip makers in three categories - the characteristics of the available modes, the socioeconomic status of the trip maker and the characteristics of the trip.Studies investigating impact of urban from on mode choice added several land use related variables to the above list expressing density, diversity, design, accessibility to transit, distance to CBD, supply of transportation infrastructures, settlement size and pattern etc. (Cervero&Kockelman, 1997; Frank et al., 2000;Nasri & Zhang, 2019).

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Data

Data for this study have been derived from Capital Area Metropolitan Organization, Austin, Texas. Activity travel survey data 2017-2018 and Street Network of 2015 for Austin area have been used to derive necessary variables for the study (Table 1).

Table1. Types of variables and their source datasets

Type of variables	Derived variables	Source Data Set
Characteristics of trip makers	Vehicle per capita	Activity travel survey 2017-2018
	Gender	
	Income	
Characteristics of Alternatives	Time	Austin Street Network 2015 and Activity travel survey 2017-2018
	Cost/income	
Characteristics of urban form	Population density	Austin TAZ 2015 GIS data
	Employment density	
	Intersection density	Street Network for Austin and Austin TAZ 2015 GIS data
Spatial	Origin and Destination Location	Activity travel survey 2017-2018

Figure 1 is showing the correlation among the variables used for the final models. Instead of taking the cost variable directly, it has been normalized by taking the ratio of cost and income. This also has removed the problem of time and cost being highly correlated. From the correlation plot (Figure 1) it can be seen that the level of correlation between the variables is acceptablefor most variables except for the intersection density-population density pair and intersection density-employment density pair. Since these variables have significant practical significance supported by the literature (Cervero& Kockelman, 1997; Ewing et al., 2014) they have been included altogether to develop the model. Table 2 is showing the descriptive statistics of the variables used in this study.

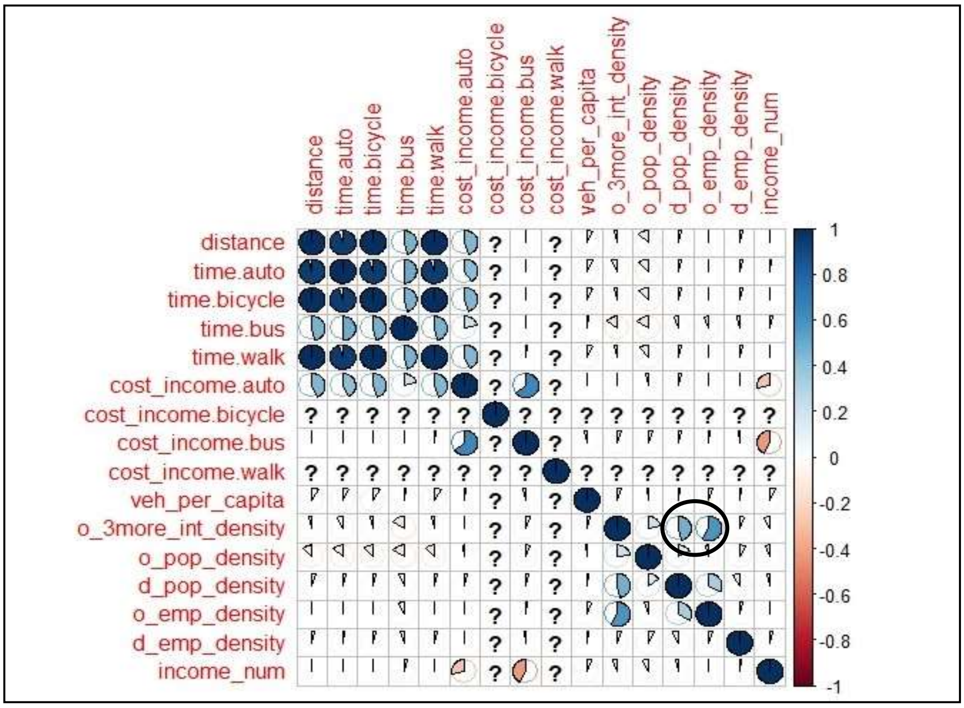

Figure 1. Correlation plot for the list of variables used for final models.

Table 2. Description of the variables

Variable Type	Variable Name	Variable Description	Count	Minimum	Maximum	Mean	Std. Dev.
Trip Characteristics	Distance	Distance travelled in the trip	20691	0.01	65.570	5.383	5.700
	time.auto	Trip time by auto	20691	0.26	70.105	7.934	6.103
	time.bicycle	Trip time by bicycle	20691	0.06	452.727	37.167	39.356
	time.bus	Trip time by bus	20691	0.07	80.166	12.052	6.922
	time.walk	Trip time by walk	20691	0.05	1144.310	103.554	107.263
	cost.auto	Trip cost for auto	20691	0.006	39.342	3.230	3.420
	cost.bicycle	Trip cost for bicycle	20691	0.00	0.000	0.000	0.000
	cost.bus	Trip cost for bus	20691	1.25	3.000	1.382	0.277
	cost.walk	Trip cost for walk	20691	0.00	0.000	0.000	0.000
	cost_income.auto	Trip cost-income ratio for auto	20691	0.00	4.738	0.065	0.161
	cost_income.bicycle	Trip cost-income ratio for bicycle	20691	0.00	0.000	0.000	0.000
	cost_income.bus	Trip cost-income ratio for bus	20691	0.006	1.200	0.029	0.051
	cost_income.walk	Trip cost-income ratio for walk	20691	0.00	0.000	0.000	0.000
Characteristics of Trip maker	gender	Gender of the trip maker: 1 = Male, 2 = Female (Categorical variable), N =20691					
	veh_per_capita	Vechicle per capita in the household	20691	0	5	0.745312	0.403851
	income_num	Income of trip maker as continuous value	20691	2.50	200.000	87.220	54.486
	income	Income of the trip maker (Categorical variable): Low = <25000, Lower-middle = >=25000 but <50000, Upper-middle = >=50000 but <100000, High = >= 100000, N = 20691					
Characteristics of Built Environment	o_3more_int_density	3-way or more intersection density at origin TAZ, per square mile	20691	0.00	401.8001	28.1884	34.2669
	o_pop_density	Populatin density at origin TAZ	20691	3.11	64712.8035	3994.7868	3529.922
	d_pop_density	Populatin density at destination TAZ	20691	0.289	444641.73	6308.080	12893.533
	o_emp_density	Employment density at origin TAZ	20691	0.00	65148.272	3460.756	6712.35
	d_emp_density	Employment density at destination TAZ	20691	0.00	263238.34	4073.822	9976.617
	o_mxd	Dummy variable: '1' if the trip is originated from mixed land use (MXD) parcel and '0' otherwise (MXD at Austin determined by Zhang et. al.,2009), N = 20691					
	d_mxd	Dummy variable: '1' if the trip destination is mixed land use parcel (MXD) and '0' otherwise (MXD at Austin determined by Zhang et. al.,2009), N = 20691					
	internal_mxd	Dummy variable: '1' if the trip is internal to a mixed land use parcel (MXD) and '0' otherwise, N = 20691					

Results

Here results of the study have been discussed in two sections- impact of urban forms on distance travelled and impact of urban forms on mode choice behavior.

Distance Travelled and Urban Forms

Descriptive Analysis

In Figure 2 it can be seen that distance travelled is decreasing significantly with the increase of population density, employment density and intersections density (better street connectivity). Distance travelled by automobile is decreasing more with the increase of density variables.

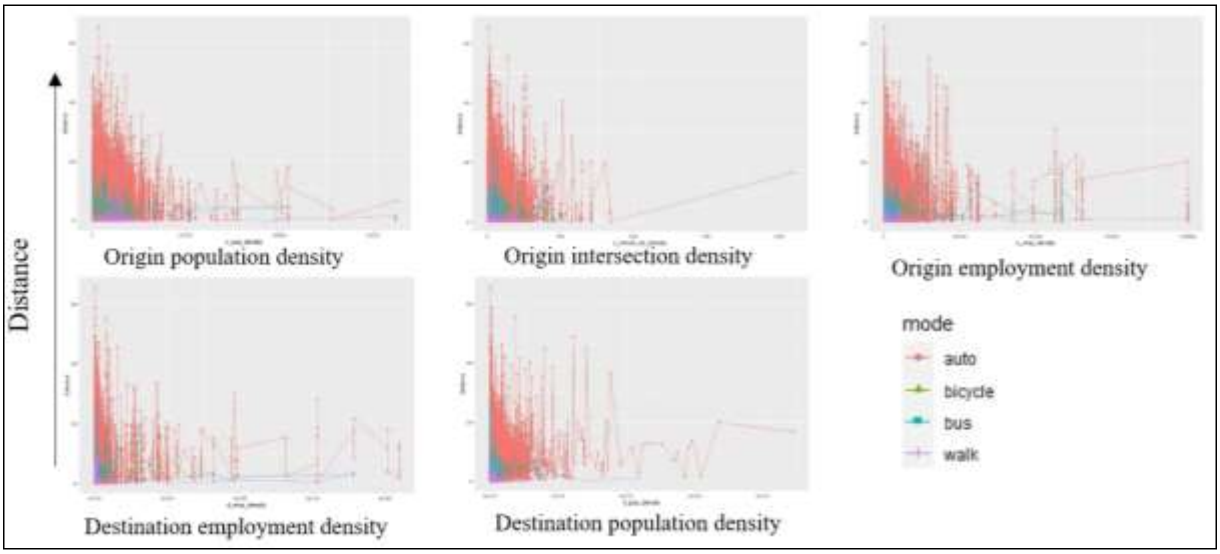

Figure 2. Distance travelled and built environment

Regression analysis

To investigate the relationship between built environment and distance travelled, two separate multiple regression models have been developed- one with only trip makers' characteristics (model 1a in Table 3) and the other including urban form variables along with previous trip makers' characteristics.

Income and vehicle ownership have been found to have positive relationship with distance travelled. Effect of income on distance traveled has been found little ambiguous. Though Distance traveled increases with the increase of income, this increase of distance travelled is more for lower-middle-income group and upper-middle-income group than high-income group compared to low-income group people in Austin.Female trip makers have been found to make shorter trips than male trip makers.

After including urban form characteristics in the model (model 1b), it has been observed that higher population density and intersection density lead to decrease of distance travelled. Model outputs regarding employment density and origin TAZ having mixed land use indicate positive relationship with distance travelled which is confusing since both literature and empirical evidence suggest negative relationship. This issue needs further investigation. Despite this issue model 1b has significantly higher adjusted R^2 value indicating a better fit than model 1a.

Table 3. Regression model for impact of urban form on distance travelled

	Model 1a (without urban form variables)		Model 1b (including urban form variables)	
Variables	Coefficients	P value	Coefficients	P value
Intercept	4.24328	< 2e-16 ***	5.140e+00	< 2e-16 ***
Characteristics of trip maker				
veh_per_capita	1.14857	< 2e-16 ***	1.143e+00	< 2e-16 ***
Income				
Low (ref.)				
Lower-middle	0.87296	2.03e-09 ***	7.704e-01	9.83e-08 ***
Upper-middle	1.00634	2.16e-13 ***	8.375e-01	8.15e-10 ***
High	0.45793	0.000701 ***	2.738e-01	0.041772 *
gender2 (female)	-0.48014	1.21e-09 ***	-4.579e-01	5.11e-09 ***
Urban form characteristics				
o_3more_int_density			-3.629e-03	0.000485 ***
o_pop_density			-1.856e-04	< 2e-16 ***
d_emp_density			1.449e-05	6.66e-12 ***
o_mxd1			1.840e-01	0.200883
Adjusted R^2	0.01133		0.02709	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*'

Mode Choice Behavior and Urban Forms

Descriptive Analysis

From Figure 3 it can be seen that number of trips by automobile is decreasing with the increase of population density, employment density and intersections density (better street connectivity). Figure 4 is also showing that origin TAZ having mixed land use (MXD TAZ) has lower share of trips by automobile and higher share of trips by bus and walk than a Non-MXD TAZ.

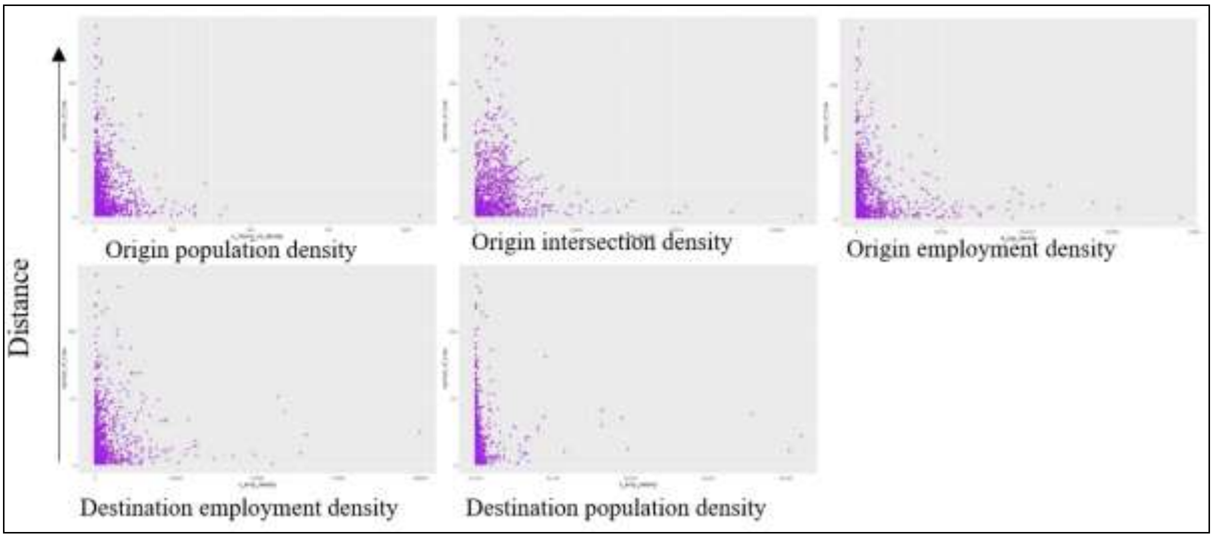

Figure 3. Number of trips by Automobile vs built environment

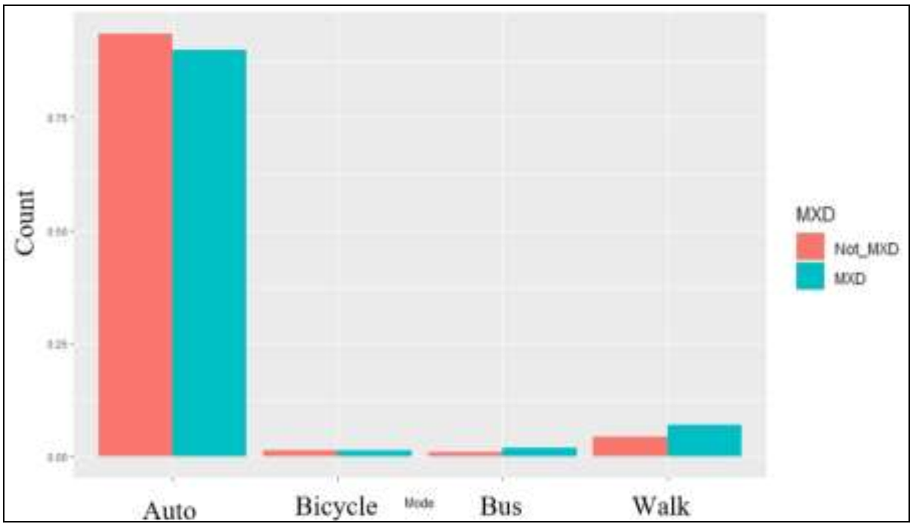

Figure 4. Mode share for MXD (mixed land-use) and Non-MXD trips

Outputs of Multinomial Logit (MNL) model

Multinomial Logit model has been estimated to investigate the impact of urban form characteristics using the variables derived from activity based travel survey 2017-2018 for the Austin area. Estimation results have been presented in Table 4. Various different model specifications have been tried to reach the final model.

The final MNL model (model 2a in Table 4) includes alternative specific variables, characteristics of trip makers, and characteristics of urban forms. There are total four choice alternatives, and 'auto' is the base category for the estimated model. The estimated coefficient for travel time conforms to the fact that modes lose utility with the increase of travel time.

Income, vehicle ownership, and gender (female) negatively correlate to choosing bus or active transportation compared to personal automobile. The probability of riding a bus decreased with increasing the person's income, and the probability of using bus decreased significantly with the increase of per capita vehicles in the household. Female trip makers ride transit or active transportation significantly less than male trip makers. This negative relationship is strong considering riding a bus. Apparently, female trip makers find the bus at Austin less suitable than male trip makers.

Bicycle, bus and walk- all has positive relationships with the density variables which suggests that increase of population density, better street connectivity (intersection density), and Mixed land use TAZ as origin and destination affect mode choice behavior in favor of bus and active transportation. Better street connectivity at origin, represented as an increase of 'three or more way intersection density' in the dataset, has a strong role in increasing the probability of riding a bus compared to personal automobile. This relationship is not statistically significant, but empirical evidence and literature support this finding. Better street connectivity also favors cycling compared to personal automobiles. The probability of using a bus also increases significantly when the origin or destination TAZ has mixed land use. The probability of walking also increases when the origin or destination TAZ has mixed land use.

MNL model 2a, which includes built form variables, is significantly a better model than Model 2b, which does not include them. All the model fitting statistics- the Log-Likelihood, AIC, and McFadden R^2 indicate a better fit for model 2a.

Table 4. Estimation results of Multinomial logit model (reference category = auto)

	Model 2a (including urban form variables)		Model 2b (without urban form variables)	
Variables	Coefficients	P value	Coefficients	P value
bicycle:(intercept)	-2.5600e+00	< 2.2e-16 ***	-2.3957015	< 2.2e-16 ***
bus:(intercept)	-2.1972e+00	< 2.2e-16 ***	-1.5961447	< 2.2e-16 ***
walk:(intercept)	-4.2894e-01	0.0010603 **	-0.0448273	0.7156078
time	-6.9582e-02	< 2.2e-16 ***	-0.0686114	< 2.2e-16 ***
cost_income	1.6293e+00	0.0027642 **	1.7586259	0.0008580 ***
Characteristics of trip maker				
bicycle:incomelower-middle	2.1665e-01	0.3857486	0.1941989	0.4362579
bus:incomelower-middle	-9.8091e-01	3.758e-08 ***	-1.0270693	4.284e-09 ***
walk:incomelower-middle	-2.3061e-01	0.0597453 .	-0.3100884	0.0104266 *
bicycle:incomeupper-middle	8.7952e-01	0.0001212 ***	0.8346226	0.0002527 ***
bus:incomeupper-middle	-1.7015e+00	4.441e-16 ***	-1.6901610	< 2.2e-16 ***
walk:incomeupper-middle	-8.2175e-02	0.4810615	-0.1587546	0.1662839
bicycle:incomehigh	2.0266e-01	0.3925022	0.1699889	0.4714220
bus:incomehigh	-1.9911e+00	< 2.2e-16 ***	-1.8783206	< 2.2e-16 ***
walk:incomehigh	-1.4166e-01	0.2052296	-0.1833685	0.0947958 .
bicycle:veh_per_capita	-1.3128e+00	1.843e-10 ***	-1.2108876	2.744e-09 ***
bus:veh_per_capita	-2.4085e+00	< 2.2e-16 ***	-2.1897951	< 2.2e-16 ***
walk:veh_per_capita	-1.0731e+00	< 2.2e-16 ***	-0.9181364	2.220e-16 ***
bicycle:gender2	-7.0617e-01	3.731e-09 ***	-0.7229512	1.471e-09 ***
bus:gender2	-2.9436e-01	0.0366583 *	-0.3067682	0.0262327 *
walk:gender2	-2.1688e-01	0.0023443 **	-0.2257946	0.0013180 **
Urban form characteristics				
bicycle:o_pop_density	-1.0633e-06	0.9511052		
bus:o_pop_density	4.1946e-05	0.0021042 **		
walk:o_pop_density	5.6298e-05	1.357e-11 ***		
bicycle:o_3more_int_density	3.4886e-03	0.0120939 *		
bus:o_3more_int_density	1.0636e-03	0.4873783		
walk:o_3more_int_density	-6.8776e-04	0.5134107		
bicycle:o_emp_density	1.3216e-05	0.0465433 *		
bus:o_emp_density	4.4575e-05	3.619e-14 ***		
walk:o_emp_density	2.9991e-05	3.953e-12 ***		
bicycle:d_emp_density	8.2595e-06	0.0001072 ***		
bus:d_emp_density	1.1484e-05	< 2.2e-16 ***		
walk:d_emp_density	7.7059e-06	0.0002239 ***		
bicycle:o_mxd1	-1.1797e-01	0.5962796		
bus:o_mxd1	4.2909e-01	0.0310698 *		
walk:o_mxd1	7.6026e-02	0.5427322		
bicycle:d_mxd1	-1.0485e-01	0.6482310		
bus:d_mxd1	6.6802e-01	0.0008539 ***		
walk:d_mxd1	2.3149e-01	0.0615350 .		
Log-Likelihood:	-5163.6		-5332.5	
AIC	10403.24		10704.94	
McFadden R^2	0.25368		0.22927	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*'

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Discussion

This study found that the urban built form has a clear and significant impact on travel behavior even after controlling the trip makers' and alternative specific characteristics. Though personal characteristics still remain important after including the built form variables, built form variables also show significant influence on distance traveled and mode choice. Urban form variables like increase in density, better street connectivity, and mixed land use TAZ as origin and destination have been found to be significant in reducing the distance traveled and car dependency. Among the characteristics of the trip makers' vehicle per capita, income and trip maker being a female have been found to increase the distance traveled. The impact of the level of income ondistance traveled helps to understand the residential location choice of the people. Though Distance traveled increases with the increase of income, this increase of distance travelled is more for lower-middle-income group and upper-middle-income group than high-income group compared to low-income group people at Austin. This indicates that the rich people find suitable places to live which is not very close to employment centers but also not very far from the employment centers. This also indicates that the middle-income group people show more tendency to live near the city periphery hence making longer trips. In the urban form model (model 1b), an increase in intersection density and population density led to a reduction of distance traveled indicating that compact city design results in shorter trips.

In the mode choice model (2a), the urban form variables were found to have significant impact on the choice of mode even after controlling other alternative specific variables and characteristics of trip makers. Model outputs suggest that increase of population density, better street connectivity (intersection density), and Mixed land use TAZ as origin and destination favors bus transit and active transportation. Among the characteristics of the trip makers' increase of income, vehicle per capita, and trip maker being a female reduce the likelihood of choosing a bus or active transportation. The influence of income and vehicle ownership on mode choice should be interpreted together. Significantly longer travel time makes the bus an inferior alternative to private automobiles in the city; hence the general tendency is that mostly the people who cannot afford private vehicles use bus transit. If the household has a car, they use it. Also, households with cars often do not consider the availability of transit when choosing their place to live, making the private automobile their only available alternative.

The results support the hypothesis of this study that mixed-use high-density development has a significant impact on the mode choice behavior of the people of the Austin area. These findings conform to the findings of researchers who found density, design, and diversity have a significant influence on mode choice behavior (Cervero&Kockelman, 1997; Ewing &Cervero, 2001; Ewing et al. 2009).

Conclusion

This study has investigated the influence of trip makers' personal characteristics and urban forms' characteristics on mode choice behavior. The findings support the claims of others (Cervero&Kockelman, 1997; Ewing &Cervero, 2001; Naess, 2012) that mixed-use, compact, and pedestrian friendly city designs can reduce the distance traveled and auto-mobile trips while promoting active transport and mass transit.City authorities aiming to reduce automobile trips and distance traveled need to consider these built form characteristics to determine suitable areas to invest in yielding the highest return in promoting transit use and active transportation. The solution for promoting transit in Austin is not only an economic but also a land use planning decision.

Though this study found a strong impact of urban form variables on distance travelled and mode choice behavior of the people in the Austin area, the findings need to be interpreted as an association rather than a causal relationship since the study used cross-sectional statistical analysis. A future longitudinal study investigating the same can confirm whether the relationship is causal or not. Moreover, due to time limitation,this study could not include several important variables to represent urban built forms such as land use diversity, access to transit, average block size, etc. This study also could not capture the fact that travel behavior has a significant spatial dimension, that both distances travelled and choice of a mode may often be influenced by the distance travelled and choice of mode by the neighbors. Developing spatial models may help to capture this spatial dimension of travel behavior.

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Conflict of Interests
The author declares no conflict of interest.

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