



Research Article

Assessment of the Impacts of Built Environment Characteristics on Trip Generation Rates of Trans-regional Commercial Land Uses: A Case Study of Mashhad City

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Article History:

Received:
13 July 2025
Revised:
10 September 2025
Accepted:
13 October 2025
Published in Issue:
31 March 2026

Abstract

Aims: This study aims to investigate the influence of built environment characteristics and physical attributes on trip generation rates for trans-regional commercial land uses. The primary goal is to identify which urban design and spatial factors most significantly affect traffic attraction in a metropolitan context, specifically within Mashhad, Iran.

Methodology: The research utilizes an extensive database of 6.8 million daily trips in Mashhad, focusing on 33 selected regional-scale commercial developments. Variables were categorized into physical attributes (e.g., land area, floor area) and built environment factors (e.g., road density, bus stop density, and shopping unit density). Data analysis was performed using descriptive statistics, correlation analysis to detect multicollinearity, and linear regression modeling to evaluate the relationships between independent variables and the average hourly trips generated.

Finding: The results indicate that trip generation is significantly influenced by four key variables: bus stop density, business unit density in the area, business unit density along streets, and total land area. Notably, the density of business units within the area emerged as the most influential positive factor. Conversely, business unit density along streets showed an inverse (negative) relationship with trip generation rates, suggesting that increased street-level density may lead to a reduction in certain types of vehicular trip attraction.

Conclusion: The study concludes that traditional trip estimation manuals, which often rely solely on physical building size, are insufficient for developing regions. Integrating built environment factors particularly public transport accessibility and local commercial density provides a more accurate forecast for traffic impact assessments. These findings offer urban planners and transportation engineers a localized framework for managing the traffic implications of large-scale commercial developments in metropolitan areas.

Keywords: Trip Generation and Attraction, Built Environment Factors, Linear Regression, Metropolitan/Regional Commercial Land Uses

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1. Introduction

Accurately understanding the trip generation and attraction rates of land uses before the construction of a development, based on the type of land use, is considered one of the preliminary steps in the process of traffic impact assessment studies. Modeling trip generation and attraction by predicting the characteristics of future trips is one of the most important stages of these studies and serves as a fundamental tool for evaluating the traffic implications of land use development.

Credible sources typically calculate trip generation and attraction rates using physical attributes of the land use, such as lot area, floor area, building density, and so on, applying these as coefficients. One of the most authoritative references is the Trip Generation Manual [1], prepared and published by the Institute of Transportation Engineers (ITE), which bases its equations on categorizing land uses and conducting extensive data collection for each category. It should be noted that the values recommended in ITE manuals are not advised for mixed-use developments such as shopping malls [2].

Numerous local studies in other parts of the world have been conducted with the aim of adjusting the coefficients proposed in this manual to achieve more accurate results. Among them is the "Study on Trip Generation and Attraction Rates for Various Land Uses in the City of Mashhad" conducted in 2012, which involved extensive data collection for seven land use groups [3].

Xiao and colleagues proposed an integrated multi-dimensional convolutional neural network with a long short-term memory (LSTM) network to analyze the spatial correlation between trip generation and land use characteristics, considering elements such as the type of residential development and proximity to central shopping areas [4]. Doulabi and colleagues used multiple linear regression to study trip generation rates in small to medium-sized urban areas of Louisiana, focusing on variables such as floor area and population density [5]. Abulneneh and others developed regression models to estimate the number of generated and attracted trips by mapping residential developments, considering factors such as household size, income, and vehicle ownership [6]. Altaaher and colleagues, reflecting on the scarcity of studies concerning trip generation for specific land uses in developing countries, conducted research to determine trip attraction rates by evaluating factors such as gross floor area and the number of employees for bank service land uses in the city of Zagazig (a city in Egypt's Sharqia Governorate) [7].

Anand and George proposed a framework for modeling trip generation using noisy and less reliable data, emphasizing the need for robust methods in such studies. Collectively,

these studies emphasize the influence of the built environment and socio-economic factors such as road network extent, public transportation systems, population density, and income levels on urban trip generation and behavior [8]. Reith and colleagues highlighted the oversight of these vital factors in past methods, which affects the accuracy of trip generation and attraction forecasting for commercial land uses in developing countries [9].

Failure to consider these factors can lead to assessments that do not reflect diverse urban conditions, potentially disrupting the balance among different travel modes and necessitating uniform design solutions.

Despite detailed planning, commercial land uses are characterized by considerable variability, involving numerous daily trips that require careful evaluation of their transportation impact. Insufficient understanding of these land uses in urban planning underscores the importance of conducting thorough traffic impact studies before their development. This research aims to investigate how built environment factors in different urban areas influence trip generation rates, utilizing extensive databases and localized studies from the city of Mashhad.

2. Literature review

Different land use configurations significantly affect the dynamics of urban components, particularly the transportation network. The complex relationship between land use and transportation is a fundamental element in urban planning, essential for the sustainable development of urban areas. When examining transportation dynamics, it is evident that factors such as neighborhood density and the availability of land use amenities play a key role in shaping urban mobility patterns. This relationship is inseparable from the overall urban transportation planning system. To simplify travel routes, reduce traffic, and promote sustainable urban growth, a deep understanding of the relationship between land use and transportation is crucial [10].

Considering the relationship between land use and transportation brings benefits such as environmental sustainability through reduced automobile dependence, economic efficiency through affordable transportation planning, enhanced public spaces promoting community interaction, reduced congestion through efficient alternatives, and improved livability in communities. This understanding is particularly important in rapidly motorizing regions like China and India for sustainable urban development [11].

In general, trip generation rate is considered a vital parameter that reflects the relationship between land use and urban transportation development. It also serves as the

starting point in the transportation planning process and traffic impact analysis [12]. From a transportation planning perspective, understanding trip generation is crucial for predicting travel patterns in a research area. Trip production and attraction refer to trips that are either generated by or attracted to a location, with the goal of predicting the number of these trips. The number of trips is calculated by relating parameters such as individual, regional, and transportation network characteristics to the number of trips [13].

Various methods have been proposed for calculating trip production and attraction. One of the standard methods in this regard is the Trip Generation Manual from the Institute of Transportation Engineers (ITE), which provides trip generation rates based on land use type and facility characteristics. This manual offers a comprehensive list of trip generation rates for more than 100 land use categories, including residential, commercial, and industrial developments. Additionally, it includes trip generation rates for various transportation modes, such as walking, cycling, public transport, and personal vehicles. The rates in this manual are based on empirical data collected from studies and surveys conducted across the United States and Canada [14]. The Urban Emissions (URBEMIS) model is another approach designed to control air pollution in California [15]. Another method is the Multi-Use Development (MXD) analysis in the U.S., which evaluates the transportation impacts of different developments. This method assesses the transportation effects of mixed-use developments [16]. The California Smart Growth Trip Generation model was developed to estimate trip generation rates for smart growth land use development projects in California. It takes into account factors such as land use composition, density, and street connectivity [17]. Additionally, Clifton and Currans at Portland State University have developed models tailored to single-family residential, multi-family residential, and retail developments, considering the specific site characteristics [18].

Numerous researchers have attempted to establish connections between various factors influencing travel behavior and the use of different transportation modes, often classifying transportation into three broad categories: private car use, active transportation (i.e., walking and cycling), and public transportation [19]. Various factors can influence travel mode choice and behavior, including environmental factors often referred to as the built environment such as distance from origin to destination, mixed land use, access to transportation networks, safety, transportation systems, road infrastructure, sidewalks, and bike paths [19]; economic factors like travel time and cost [20]; psychological factors such as attitudes, goals, and habits [21]; demographic and socio-economic factors like

age, income level, employment status, and service indicators such as available parking spaces and public transportation frequency [22].

From a transportation policy perspective, having a better understanding of factors such as private vehicle ownership and car usage is crucial in land use planning and forecasting, as well as in formulating transportation and economic policies to reduce traffic congestion and environmental pollution through lower dependence on private vehicles [23]. In this regard, previous studies have identified socio-economic factors, built environment factors, vehicle characteristics, and related costs as critical influences on car ownership and usage.

Regarding the built environment, the concept of creating dense cities to encourage households to reduce their personal vehicle use and drive less has been widely accepted among researchers [24]. Households living in areas with good public transportation coverage are less dependent on personal cars [25]. Areas with high bicycle lane density and sufficient infrastructure for active transportation reduce the appeal of private cars [26]. Moreover, the desire to use private vehicles is lower in residential areas with commercial centers [24]. On the other hand, adequate parking provision [27] and travel distance [28] can increase car ownership and usage.

Built environment factors such as density, land use, and road network connectivity encourage walking and cycling over short distances [29] and increase the duration of active transportation [30]. Other studies show that areas with high density, proximity to the city center, local amenities, mixed land uses, walkability (availability and ease of access to proper sidewalks), high public transportation density, and diverse transportation systems encourage walking and cycling [31].

Additionally, physical factors such as gross floor area and factors related to the built environment of shopping centers, such as sufficient parking provision, number of employees, and number of retail units, influence the attraction of trips to commercial land uses and shopping centers [2, 32-37].

New regional research in Iran and the Middle East is providing a more accurate picture of trip generation that better fits the cultural and physical context of these cities. In Mashhad, for example, the use of Multiscale Geographically Weighted Regression (MGWR) has shown that the effect of built environment variables on trip generation is heterogeneous at the neighborhood level, and that global models may conceal some of this variability [38]. In Tehran, the application of a Multilayer Perceptron (MLP) network to predict active travel behavior serves as a successful example of using machine learning methods in an Iranian context. This research highlights the importance of built environment and accessibility

variables, alongside demographic characteristics, in determining travel patterns [39]. Comparative studies in Cairo, Istanbul, and Tehran reveal that work and non-work travel patterns differ significantly in these cities. This finding underscores the necessity of contextualizing trip generation rates to align with local conditions [40]. Urban studies in Iran, such as research conducted in Rasht, demonstrate that the configuration and structure of the urban fabric play a significant role in altering the share and volume of pedestrian trips. These findings confirm the importance of urban design in promoting walking [41]. Furthermore, the evaluation of public infrastructure and transit performance in Mashhad has been highlighted as a critical factor in urban functionality, with studies emphasizing the role of specific bus lines and their spatial coverage in the city's transport network [42]. A study conducted in a medium-sized Palestinian city (2024) in the Middle East, using household data, revealed that local trip generation rates substantially differ from those reported for developed countries. This finding underscores the necessity of localizing these relationships for commercial land uses as well [43].

In parallel with these developments, the international literature from 2023 to 2025 has shifted toward more advanced methods. In the field of commercial land uses, new research on shopping centers has provided specialized models for estimating trip volume. These models incorporate not only the building's gross floor area but also its functional and contextual characteristics [44].

New data sources, such as mobile phone location data, have made trip generation estimation faster and more accurate. These sources not only enable the analysis of temporal changes but also provide greater accuracy in certain categories compared to manual ITE methods [45]. Ultimately, the relationship between public transport accessibility/station density and trip generation outcomes (particularly the reduced reliance on private cars) has been strengthened within Transit-Oriented Development (TOD) frameworks. This established connection supports the interpretation of the role of bus station density in our study's results and helps clarify the path for formulating relevant policy recommendations [46].

Research Gap: Previous studies do not consider the simultaneous impact of physical factors and the built environment on the trip production/attraction rates of shopping trips. Therefore, this research aims to model the trip generation rates for commercial land uses while considering the impact of these two factors.

3. Research data

The aim of this study is to investigate the relationship between the trip generation rate of commercial land uses

and the performance of the interregional area, as well as the physical characteristics of the land use and the built environment of their location. This type of land use includes those that have an operational radius and sphere of influence extending beyond the boundaries of a single region, and they perform functions at the regional, city, and metropolitan levels (Center for Studies and Urban Planning of Tehran, 2011). Therefore, the number of trips made to a land use is considered as the dependent variable, and the variables representing the physical characteristics of the land use and the features of the built environment where the land use is located are considered as independent variables.

3.1. Study area and data collection

Mashhad, the second largest metropolitan city in Iran, with a population of approximately 3.4 million people residing in 353 urban neighborhoods as of 2021 [47], is the study area for this research. Mashhad's rapid urban expansion and changes in its physical structure over recent decades have significantly altered land use patterns and transport demands, necessitating localized studies on trip generation [48]. The extensive database of the Transportation Network Management and Engineering Organization forms the basis of this study. This database shows a total of 6.8 million trips on a weekday. The composition of trips in the city, based on different trip purposes, is shown in Figure 1.

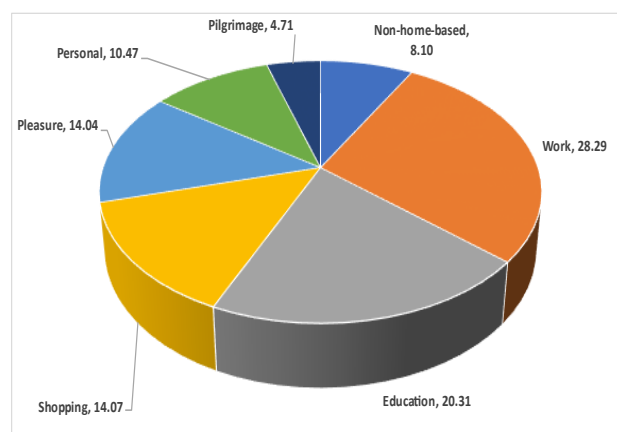


Figure 1. Daily Trip Composition of Mashhad City

As observed, the share of commercial trips from the total daily trips is 14%. Therefore, paying attention to commercial trips and understanding their characteristics is of particular importance.

As discussed in previous sections, this issue is the reason for defining the subject of the present study.

Although the dataset comprises 33 commercial land uses, this sample size meets the minimum statistical requirement for regression modeling.

Moreover, data collection in a large and complex city such as Mashhad is constrained by access, cost, and administrative limitations. Nonetheless, the sample reflects a diverse distribution of commercial uses across the city. The 33 sites were selected based on three main criteria: (i) commercial user type (e.g., retail, wholesale, services), (ii) geographic coverage to represent different neighborhoods, and (iii) variations in traffic volume. This strategy ensured that the dataset captured both spatial and functional diversity of commercial land uses in Mashhad.

3.2. Geographical and statistical considerations

Defining an appropriate spatial scale to capture the actual variability and interdependencies between urban factors is crucial [49]. The importance of selecting an independent and distinct geographical area that accurately represents the built environment in transport and land use studies is significant. This approach ensures that spatial heterogeneity in the built environment, which can significantly affect travel behavior, is adequately modeled. Following these guidelines, this study uses statistical areas similar to census areas to define environmental conditions [50]. This methodological choice is supported by the use of neighborhood units, which are often used as approximations for environmental conditions in travel behavior studies [51, 52].

By using these defined areas, regression analysis can effectively reflect realistic urban configurations and interactive patterns that are essential for accurately modeling the impact of land use and socio-economic factors on trip generation. It is essential to note that in urban planning studies, the term "region" refers to a broad

sub-region in the study area of the city that shares common characteristics. These shared characteristics may include factors such as topography, climate, population density, settlement patterns, dominant economic activities, or cultural identity.

In urban transportation studies, each region is further subdivided into smaller areas, which act as trip generation and attraction centers. Ideally, each area is designated for a specific land use, such as residential, commercial, industrial, or recreational.

However, in practice, the distribution of land uses across the city often results in mixing within each area due to the lack of regulated zoning policies. For example, Mashhad is specifically divided into 12 regions and 353 traffic zones, as shown in Figure 2.

Figure 2 also shows the locations of 33 selected commercial land uses within the city.

3.3. Selection of variables

Table 1 shows the titles of the variables examined in this study.

4. Descriptive analysis

The subject of descriptive statistics involves organizing and classifying data, graphical representation, and calculating values such as the mode, mean, median, and others, which reflect the characteristics of each member of the population being studied.

Table 2 shows the descriptive statistics of the research variables, including the minimum value, maximum value, mean, median, standard deviation, skewness, and kurtosis.



Figure 2. Mashhad's zoning map and locations of selected commercial uses

Table 1. Descriptive variables for trip generation rate of each commercial use

Variable group	Variable name	Description	Unit	Symbol
Physical	Land Area	Total land area of the commercial use	m ²	Land_Ar
	Floor Area	Total building area of the commercial use, including external walls	m ²	GFA
Hourly Trip	Average Trip	Average hourly trips generated and attracted to the land use	trips	Trip
	Average Trip per 100 square meters	Average trips per 100 square meters of land use area (floor area)	trips/100 m ²	Trip_pr_100sqm
Built Environment	Road length density	Average total length of roads per one hectare of the zone of the commercial use	m/ha	Rd_Ln_Densi
	Road surface ratio	Ratio of total road surface in the zone of the commercial use to the zone area	m ² /m ²	Rd_Srf_rati
	Asphalt surface ratio	Ratio of total asphalt road surface in the zone of the commercial use to the zone area	m ² /m ²	Asph_Serf_rati
	Number of parking lots	Number of on-street parking lots in the zone of the commercial use	lots	Park_Lot
	Parking area ratio	Ratio of total on-street parking area in the zone of the commercial use to the zone area	m ² /hectares	Park_Ar_rati
	Parking density	Average number of on-street parking lots per one hectare of the zone of the commercial use	lots/ha	Park_Lot_Densi
	Number of bus stops	Number of bus stops in the zone of the commercial use	stops	Bus_Stop
	Bus stop density	Average number of bus stops per one kilometer of line length in the zone of the commercial use	buses	Bus_Stop_pr_km
	Bus Stop Density in the Area	Average number of bus stops per one hectare of the zone of the commercial use	Buses	Bus_Stop_Densi
	Number of shopping units	Average number of shopping units per one hectare of the zone of the commercial use	units	Shop_Unit_pr_ha
Shopping Unit Density	Average number of shopping units per one kilometer of road length in the zone of the commercial use	units	Shop_Unit_pr_Km	

Table 2. Descriptive Statistics of the Research Variables

Variable Category	Variable Symbol	Mean	Median	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
Physical Land Use	Land_Ar	3425.15	1940.00	3952.77	2.68	7.65	270.00	18000.00
	GFA	9182.33	3600.00	16061.97	3.79	16.22	853.00	85000.00
Trip Generation	Trip	962.30	399.00	1713.19	3.23	10.28	69.00	7723.00
	Trip_pr_100sqm	14.82	12.12	11.81	1.08	1.03	1.34	46.27
Built Environment	Rd_Ln_Densi	95.47	88.33	29.56	0.41	-0.76	41.30	158.18
	Rd_Srf_rati	0.28	0.29	0.07	0.02	-0.93	0.17	0.40
	Asph_Serf_rati	0.13	0.13	0.04	-0.05	-0.55	0.05	0.19
	Park_Lot	1235.38	1161.87	664.73	1.13	2.28	42.80	3148.72
	Park_Ar_rati	253.46	238.87	128.79	-0.03	-0.74	6.48	499.93
	Park_Lot_Densi	16.90	15.92	8.59	-0.03	-0.74	0.43	33.33
	Bus_Stop	15.21	14.00	8.09	1.53	3.18	4.00	43.00
	Bus_Stop_pr_km	5.86	3.67	5.05	1.89	2.21	1.65	19.96
	Bus_Stop_Densi	18.85	18.92	6.87	1.30	5.08	6.93	44.45
	Shop_Unit_pr_ha	10.32	8.07	7.68	1.69	3.58	1.08	36.73
Shop_Unit_pr_Km	111.49	88.46	73.46	1.25	2.13	8.25	343.16	

5. Correlation analysis between variables

Due to the large number of variables in the study, not all pairwise correlations were reported. Instead, the correlation of the dependent variables of the research was analyzed separately within each subgroup of physical factors and the built environment.

Figure 3 and Figure 4 are designed in such a way that the histogram along with the density curve is plotted along the diagonal.

Above the diagonal, the Pearson pairwise correlation values between the variables are displayed. Additionally, below the diagonal, scatter plots for each pair of variables are presented.

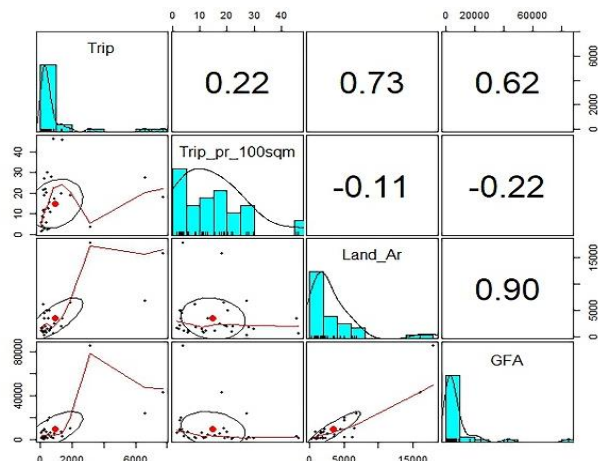


Figure 3. Correlation analysis correlation analysis for physical variables

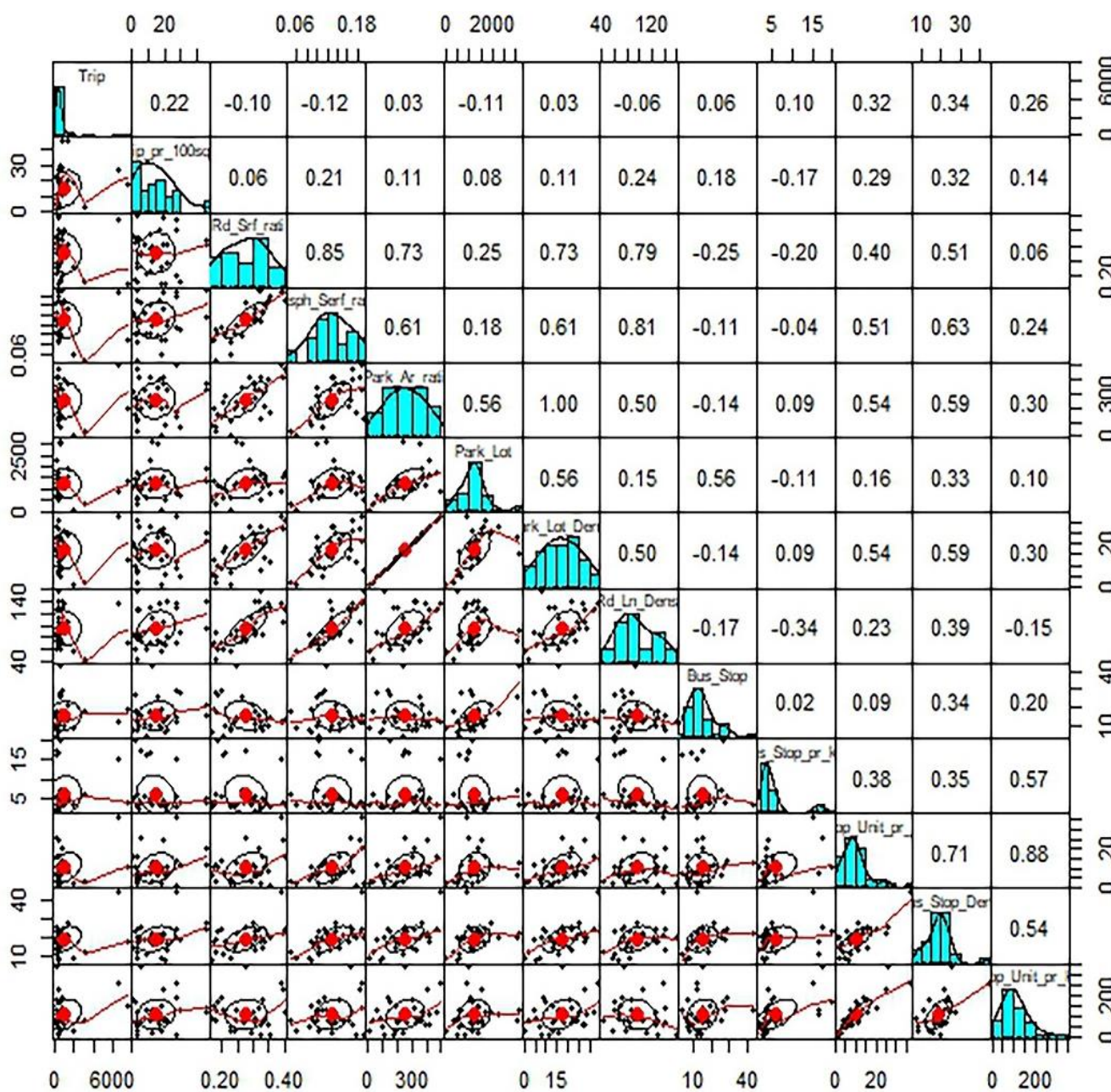


Figure 4. Correlation analysis in the subgroup of built environment factors

As seen in [Figure 4](#), the two variables "Parking Area Density in the Zone" and "Parking Spot Density in the Zone" show a perfect correlation with each other. Due to multicollinearity, it is not possible to include all the variables in the final models. Only one of these two variables can be considered in the final model. The variable "Parking Area Density in the Zone" was chosen for the final model due to its relative comprehensiveness compared to other variables in its category and its greater accessibility for the final model.

6. Prediction using linear regression models

Linear regression has a long history in transportation planning studies and is currently used as an important tool for analyzing and examining the relationships between variables and the factors influencing travel by researchers. Linear regression allows researchers to assess the impact of different variables on travel behavior [\[53\]](#). In another study, regression methods were used to analyze changes in travel behavior and identify significant points of change in travel patterns [\[54\]](#). Other studies in this field include trip production estimation [\[55\]](#), estimating travel production for transportation infrastructure near mixed-use developments [\[56\]](#), bicycle trip models using weighted regression [\[57\]](#), the impact of habits, motivations, attitudes, and driving norms on travel goals in daily car use [\[58\]](#), the impact of significant factors on metro trips in Madrid [\[59\]](#), and more.

Therefore, in this section, linear regression models were used to identify the most important variables influencing the dependent variable.

One of the assumptions considered in regression is the independence of residuals (the difference between actual values and the values predicted by the regression equation). If this assumption is violated, it may indicate the presence of unrecognized patterns in the data, leading to incorrect estimations. To examine the independence of residuals, the Durbin-Watson test is applied. The test statistic ranges from 0 to +4, and if the statistic falls between 1.5 and 2.5, the null hypothesis (no correlation between residuals) is accepted. Otherwise, the null hypothesis is rejected, indicating correlation between residuals.

Additionally, if two predictor variables have a high correlation, such as 0.90, they explain the same variance in the dependent variable.

This phenomenon is called multicollinearity, which is an important issue that must be avoided in multivariate analysis. To check for multicollinearity, the tolerance statistic and Variance Inflation Factor (VIF) are used. The tolerance statistic represents the proportion of total variance not explained by other variables and is calculated

as $1 - R^2$. A tolerance value less than 0.1 indicates multicollinearity. Another issue with multicollinearity is that the high correlation between predictor variables increases the standard error of their coefficients, meaning the values of these variables fluctuate greatly from one study to another. This is known as the Variance Inflation Factor (VIF). VIF values greater than 10 indicate that the variable is redundant. Linear regression was employed in this study because of its interpretability and established use in transportation planning practice. However, the authors acknowledge that more advanced approaches such as neural networks, ensemble machine learning models, or multilevel frameworks could capture nonlinearities and hierarchical effects. These will be explored in future research as more extensive datasets become available. Multicollinearity was examined using the Variance Inflation Factor (VIF). Variables with VIF values greater than 10 were considered problematic and removed (e.g., parking density vs. parking area). Importantly, the analysis confirmed that the removal of these variables did not alter the significance of the remaining predictors, thus preserving the stability of the model.

6.1. Relationship between travel and physical parameters

According to [Figure 3](#), among the category of hourly travel variables, the "average trip" variable, which showed a stronger dependency with physical variables, was selected, and "average trip per 100 meters" was excluded from the analysis.

Furthermore, based on [Figure 3](#), the two parameters, "land area" and "gross floor area," had a high dependency with each other; therefore, each of them was examined separately using linear regression models.

The diagnostic statistics and summary of the regression model for the Land Area variable are presented in [Table 3](#). The results indicate a significant relationship, with an R-square of 0.533. The corresponding regression coefficients, including t-statistics and confidence intervals for this model, are detailed in [Table 4](#).

Subsequently, the performance of the Gross Floor Area (GFA) as a predictor was evaluated. [Table 5](#) summarizes the model diagnostics for GFA, while the specific coefficients and significance levels for this relationship are reported in [Table 6](#).

Based on the Durbin-Watson statistics shown in both [Table 3](#) and [Table 5](#), the independence of residuals is confirmed for the developed models.

Although both equations have average indices, as seen in the tables above, the land area model has better indices than the gross floor area model.

6.2. Relationship between travel and physical and built environment variables

To obtain an appropriate model, the "average trip" was considered as the dependent variable, and the other physical and built environment variables were treated as independent variables. The model was selected using the stepwise model selection method with an entry criterion of

0.1 and an exit criterion of 0.15. The estimates obtained are summarized in Table 7 and Table 8. The significance values for accepting the t-test depend on various factors [60]. Considering the exploratory nature of the research, significance values with a 10% acceptance level are acceptable and can be accepted [61]. If a 5% significance level is considered acceptable, the results of the linear model analysis will be as shown in Table 9 and Table 10.

Table 3. Regression Model Summary and Diagnostics

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.730a	.533	.518	1189.07252	.533	35.427	1	31	.000	1.430

a. Predictors: (Constant), Land_Ar, b. Dependent Variable: Trip

Table 4. Regression Coefficients and Confidence Intervals

Model	Unstandardized Coefficients		Standardized Coefficients(β)	t	Sig.	90.0% Confidence Interval for B		VIF
	B	Std. Error				Lower Bound	Upper Bound	
Constant	-121.82	275.719		1.000	.662	-589.308	345.667	
Land_Ar	.317	.053	.730	5.952	.000	.226	.407	1.000

Table 5. Regression Model Summary and Diagnostics

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.622a	.387	.367	1362.99169	.387	19.556	1	31	.000	1.693

a. Predictors: (Constant), GFA, b. Dependent Variable: Trip

Table 6. Regression Coefficients and Confidence Intervals

Model	Unstandardized Coefficients		Standardized Coefficients(β)	t	Sig.	90.0% Confidence Interval for B		VIF
	B	Std. Error				Lower Bound	Upper Bound	
(Constant)	353.166	274.351		1.287	.208	-112.002	818.334	
GFA	.066	.015	.622	4.422	.000	.041	.092	1.000

Table 7. Regression model summary and diagnostics

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
				R Square Change	F Change	df1	df2	Sig. F Change	
.868a	.753	.718	910.28032	.753	21.337	4	28	.000	2.730

a. Predictors: (Constant), Land_Ar, Shop_Unit_pr_Km, Bus_Stop_Densi, Shop_Unit_pr_ha

b. Dependent Variable: Trip

Table 8. Regression coefficients and confidence intervals

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error				Tolerance	VIF
(Constant)	-1715.151	565.171		-3.035	.005		
Shop_Unit_pr_ha	114.928	56.860	.515	2.021	.053	.136	7.362
Bus_Stop_Densi	66.015	34.850	.265	1.894	.069	.452	2.214
Shop_Unit_pr_Km	-8.534	4.977	-.366	-1.715	.097	.194	5.162
Land_Ar	.350	.042	.807	8.402	.000	.955	1.047

Table 9. Regression model summary and diagnostics

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				Durbin-Watson	
				R Square Change	F Change	df1	df2		Sig. F Change
.847b	.717	.698	941.38860	.184	19.458	1	30	.000	2.590

a. Predictors: (Constant), Land_Ar, Bus_Stop_Densi

b. Dependent Variable: Trip

Table 10. Regression coefficients and confidence intervals

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error				Tolerance	VIF
(Constant)	-2221.712	523.701		-4.242	.000		
Land_Ar	.338	.042	.779	7.972	.000	.987	1.013
Bus_Stop_Densi	107.553	24.382	.431	4.411	.000	.987	1.013

As can be seen, all the values related to the model variables and the model structure are acceptable. Compared to other models, this model is superior and can explain 72% of the variance in the response variable. Among the built environment variables, the public transport station density (bus stations) and the business unit density are included in the model. An interesting observation is the impact and relationship between them and the average trips made by commercial users. As seen, increasing the density of business units in an area increases the number of trips made to that area, which makes the area a stronger retail area compared to other urban areas. However, increasing the density of business units along a street leads to a reduction in trips made for shopping purposes to that location.

An interesting outcome of this study is the inverse relationship between the density of commercial units along streets and the number of generated trips. This finding can be explained by several mechanisms: (i) higher commercial density increases the likelihood of walking trips, (ii) dense urban corridors encourage the use of public transport instead of private vehicles, and (iii) mixed-use conditions facilitate internal capture of trips within neighborhoods. Together, these mechanisms reduce the number of external vehicle trips generated by dense commercial strips. This interpretation is consistent with evidence discussed in the Literature Review section, where regional and international studies reported similar effects of density and mixed-use development on reducing motorized trip generation.

7. Conclusion

In this study, the aim was to examine the characteristics of the built environment as an independent parameter, alongside the physical characteristics of land use.

For this research, large-scale commercial land uses were selected, which typically have the highest demand for construction outside of approved detailed urban and

regional plans. These land uses have the most significant impact on traffic due to the substantial amount of movement they generate in the area.

The findings of this study were based on data for 33 land uses with specific characteristics in the city of Mashhad. According to the research methodology, this number represents the minimum required sample size, and due to data limitations, it was not possible to consider more samples.

7.1. Findings of the study

Some of the important contributions of this study include demonstrating the impact of environmental characteristics alongside the physical characteristics of land uses, and understanding how these factors influence travel behavior. Other key findings are as follows:

- In this study, aside from the land use area, the land area of the project was also considered as part of the physical characteristics of the land uses.
- The results from the modeling indicate that, among the two physical variables related to commercial land uses, the land area is more suitable for estimating trips for commercial land uses than the built-up area.
- In this study, 11 characteristics of the built environment were examined that could influence the generation of trips for large-scale commercial land uses.
- Among all the built environment variables, the density of bus stops in the area, along with the land area of the land use, produced the best results in the linear regression modeling.
- In addition to the density of bus stops in the area, the density of business units along the streets and within the area also had an impact on trips for large-scale commercial land uses. Specifically, the density of business units along the street led to a reduction in trips, whereas the density of business units within the area around the land use led to an increase in trips.

- Of all the built environment variables, the density of business units within the area had the greatest impact on the average trips generated by the land use.

7.2. Recommendations for urban planners

The results emphasize the importance of considering spatial and built environment factors in urban planning and traffic management. This study suggests that traffic management strategies should be based on the development of public transportation, particularly buses.

7.3. Suggestions for future research

- Expanding sample size and diversity: Future studies could explore a broader geographical scope and a more diverse range of commercial land uses to enhance the generalizability of the findings.
- Longitudinal analysis: Conducting longitudinal studies could help in understanding how the built environment influences travel generation over time.
- Incorporating additional built environment variables: While this study focused on a few built environment factors, future research could include additional variables such as walking distance to stations, public transport quality, and parking availability at land use sites for visitors, to deepen socio-economic analyses.
- Advanced traffic simulation models: Using advanced simulation models could provide more accurate insights into the specific contributions of built environment configurations to traffic patterns.
- Impact of public policy: Investigating the impact of specific urban planning policies on the effectiveness of commercial land use planning and its effects on traffic could provide practical insights for policymakers.

These insights will contribute to a more informed approach to urban development, helping policymakers design urban environments that effectively address the complexities of traffic congestion and land use planning. As cities continue to grow and evolve, such research is crucial for developing integrated strategies that consider the complex relationships between land use features and travel behavior. Future research could also integrate advanced machine learning and multilevel approaches, building on the recent international and regional studies cited in the Literature Review, in order to capture more complex and nonlinear relationships in trip generation modeling.

Acknowledgments

The authors would like to express their sincere gratitude to the Transportation and Traffic Organization of Mashhad

Municipality for providing the comprehensive travel database and spatial data that made this research possible. We also thank the experts who provided technical insights during the data collection and analysis phases.

Authors Contribution

All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests

The author states that there is no conflict of interest.

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