

Article

The Influence of Origin Attributes on the Destination Choice of Discretionary Home-Based Walk Trips

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Abstract: Walking has been recognized as an important mode of transportation in recent years, and recent research has improved travel demand models for walk trips. One important added stage is the distribution of walk trips, which can be evaluated using destination choice models. Previous studies have overlooked the importance of origin trip attributes in the destination choice of walk trips. With the aim of improving destination choice models for discretionary home-based walk trips, a questionnaire based on the previous day's walk trips was used, and 422 trips were collected from individuals. A discrete choice logit model is used for discretionary trips by utilizing policy-related variables, such as origin-sensitive variables, land-use-related variables, and socio-economic conditions of individuals. Additionally, a solution is proposed to address the issue of data scarcity in considering the choice set. The results demonstrate that origin land-use (LU) variables, such as LU diversity index and access to green spaces, as well as socio-economic variables, like age and homeownership status, are statistically significant in the destination choice of discretionary home-based walk trips. One prominent result is that reducing the diversity of unattractive LU compared to increasing the diversity of attractive LU has a greater impact on the destination choice of such trips. Specifically, a 1% increase in the diversity of attractive LU in the origin area leads to a 0.031% increase in the probability of choosing a destination within that area, while a 1% decrease in the diversity of unattractive LU results in a 0.124% increase in the probability of choosing a destination within the area. The findings can be utilized in urban LU distribution and assessing their impact on destination choice for walk trips, ultimately informing future urban planning efforts in the context of pedestrian mobility.

Keywords: destination choice; walking trips; four-step demand model; discretionary trips



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1. Introduction

In recent years, the problems arising from car-oriented approaches and their consequent environmental, health, psychological, and social issues have led to the adoption of new approaches to the design of urban streets. It involves comprehensive planning and prioritization strategies focused on sustainable and active modes of transportation [1]. The shift toward sustainable transportation has captured the attention of urban planners and policymakers, with non-motorized modes of travel, such as walking and cycling, gaining significant focus [2,3].

Walkable neighborhoods with high density, mixed uses, and good street design encourage walking, but personal choices also matter [4]. Pedestrian needs in a walkable neighborhood encompass safety features, like crosswalks and lighting; facilities, such as seating and shade; and infrastructure, like wayfinding signs and public restrooms, to enhance the pedestrian experience and promote walking [5].

Theoretical frameworks in urban morphology suggest that cities' physical form and structure significantly influence travel behavior, including pedestrian movements [6]. These

theories highlight the importance of considering urban design elements, such as street connectivity, LU patterns, and spatial configuration in modeling pedestrian travel behavior. Similarly, theories from human behavioral geography emphasize the role of individual and collective spatial behaviors in shaping travel choices, suggesting that personal and social motivations and environmental perceptions are critical in understanding walk trip distributions.

Modeling walk trips in the transportation planning process has always been faced with numerous challenges. In many conducted studies, the modeling of pedestrian travel behavior is often neglected, and walk trip (WT) information is not adequately considered [7]. However, considering the importance of pedestrian travel behavior and the necessity of planning, designing, and maintaining urban streets with a focus on active and sustainable modes of transportation, new approaches have been developed to incorporate WTs. Some of these approaches have focused on identifying factors that influence WT production [8]. Moreover, with the increased accuracy of pedestrian travel behavior data, newer approaches have emerged that encompass the modeling stages of WT distribution [9–11].

While simpler models, such as growth models and gravity models, can be used for WT distribution, planning for WTs requires considering their sensitivity to various variables and ensuring temporal sustainability. The lack of sufficient research highlights the need for further studies in the field of destination choice modeling for WTs and the identification of influential factors, given their innovative nature and importance. The innovative nature of destination choice modeling for WTs lies in its ability to capture the diverse preferences and behaviors of pedestrians within urban environments.

The purpose of the trip heavily influences the desire to walk. As reported [12], the most common purpose for walking or cycling in the United States is for “social/recreational” trips. Following social/recreational trips, the most prevalent purposes for walking trips include personal/family errands, shopping, visiting friends and relatives, and school/religious purposes. Therefore, modeling discretionary WTs is important among the various purposes of walking trips.

In the context of transportation planning, demand management policies aim to reduce demand, while economic and urban management perspectives seek to increase discretionary trip demand. Considering this paradox, punitive policies for private vehicles are suitable only for mandatory trips, while it is preferable to implement incentive policies for alternative modes of transportation for discretionary trips. For example, implementing a toll policy for private vehicles, which is a punitive action, can steer users towards walking for mandatory trips. However, implementing punitive policies in recreational, historical, and tourist areas may discourage travelers, leading to negative economic and social consequences. Implementing incentive policies for WTs requires the identification of influential variables and planning based on them. Furthermore, a considerable portion of discretionary trips is allocated to recreational, tourist, historical, and religious destinations, and these trips can play a substantial role in promoting urban economics. Therefore, modeling discretionary WTs can also be beneficially utilized.

Planning based on the influential variables in the destination choice of discretionary WTs can increase the attractiveness of walking and have a considerable impact on individuals’ choices and the promotion of walking as a mode of transportation. For instance, the likelihood of choosing walking for discretionary trips is higher among older adults compared to other age groups, and the aging population in many developing countries emphasizes the need for policymakers to pay attention to the goals of discretionary WTs within this age group [13].

Improving the outcomes of destination choice models in the context of discretionary WTs is crucial in four key areas: identifying latent and observable variables [14,15], the type of discrete choice model (such as Logit, Probit, and other models), and addressing heterogeneity in destination choice models [16,17] as well as considering choice sets [18–20]. The primary objective is to enhance the destination choice model to identify origin-related features of WTs. Also, identifying and analyzing the sensitivity of variables and focusing

on making discretionary WTs more appealing are other aims of this research. Identifying the influential factors on the overall distribution of trips (urban characteristics, such as LU distribution, and socio-economic variables, such as income levels) and assessing the degree of their impact are among the objectives. Additionally, this paper aims to propose a new approach to consider choice sets and identify observable variables. Key questions addressed include the influence of policy variables on the destination choice of WTs, the extent of their impact, and potential solutions to address data scarcity in the destination choice model.

The innovation is significant in three aspects. Firstly, it utilizes policy-related variables and variables that can enhance the sustainability over time of destination choice models. Additionally, in trip distribution and destination choice models, efforts are made to make the models sensitive to destination variables. However, the emergence of variables as alternative-specific (rather than alternative-generic) variables has made the destination choice model sensitive to origin variables, allowing for the measurement of their value and impact. Moreover, in modeling, separately considering origin and destination characteristics for different areas requires a large number of samples. However, another innovation lies in the method of examining individuals' choice sets, which has been accomplished using a small number of samples (422 samples in this paper).

The direct application of this research is to incorporate WT distribution models as an added stage to the classic four-step travel demand models. Having models that are sensitive to socio-economic characteristics, origin attributes (such as built and natural environment), and attitudinal variables for WT distribution can be instrumental in analyzing topics such as the impact of LU density, LU diversity, urban design, distance to public transportation stops, and travel demand management on destination choices and pedestrian behavior. Therefore, it provides a highly valuable tool for further analysis in urban development studies.

2. Literature Review

In analyzing travel distribution models, understanding the factors influencing trip distribution and establishing frameworks for trip distribution by traffic analysis zones are paramount [21]. While studies based on origin-destination questionnaires may not require a focus on base-year distribution models, utilizing current distribution structures is essential for future trip distribution modeling [22].

Early studies on WT distribution models focused on developing and testing travel models for predicting destination and shopping route choices in urban centers [23]. However, these studies were limited to city centers and did not consider the influence of built environmental characteristics on destination choices. Subsequent research proposed new models for walk destination and mode choice, including destination choice for non-motorized modes, like walking and cycling [24]. These models identified significant factors such as the difficulty of non-motorized travel and pedestrian environmental factors influencing destination choices.

Some studies focused on the destination choice model by pedestrians [9,10,18,24]. Clifton et al. developed a destination choice model based on distance, pedestrian index of environment, size, barrier to walking, and travelers' characteristics. A sampling method was proposed to generate a more realistic choice set, and models were developed [18]. The research was conducted on the behavior of specific trip generators, like dormitory students in non-mandatory walking trips. These studies have not investigated the effect of origin attributes and route on destination choice.

Much research has been done to find influential factors and variables in pedestrian behaviors [25–27]. The majority of the research highlighted the importance of the built environment on pedestrian behaviors [28–30]. Distance also affects the pedestrian behaviors [26,31]. To consider LU diversity, population density, commercial density, and intersection density in research, Peiravian et al. introduced a pedestrian environment index [32]. This index is a simple quantity to measure the walkability of a zone. The measure of the accessibility of public space networks, called configurational accessibility, is shown

to be influential on the proportion of pedestrian trips and overall trips [33]. In addition, the existence of similar facilities at the origin or features of the route may influence the destination choice. Some meaningful variables (e.g., configurational accessibility) in other models have not been statistically examined in walk destination choice models.

Previous studies have investigated destination attributes and variables [9,18,24]. These studies typically adopt a modeling approach that defines variables within utility functions in alternative-generic forms. However, to our knowledge, there is a scarcity of research utilizing destination alternative-specific variables. This creates a notable research gap in the field, as it overlooks the origin-related attributes of destinations.

Promoting walking as a mode of transportation is gaining attention from urban planners and policymakers due to its numerous benefits, including improved public health, reduced congestion, and lower environmental impact [26,34]. Discretionary walking, which refers to walking trips undertaken for leisure, recreational, or non-essential purposes, has emerged as a focal point in transportation research [27]. This trend has been observed in recent studies such as those conducted by Macioszek et al., which underscores the importance of understanding and promoting discretionary walking within urban environments [31]. Regarding the aforementioned importance of discretionary trips, limited studies have demonstrated the influence factors that influence these trips.

3. Methodology

Figure 1 shows the research process. After identifying research objectives and the literature review, a questionnaire based on the previous day's WT was designed, and then the collected data were refined and corrected. Considering the research objective, home-based WTs with discretionary purposes were separated from other trips. Then a choice set was constructed for use in modeling.

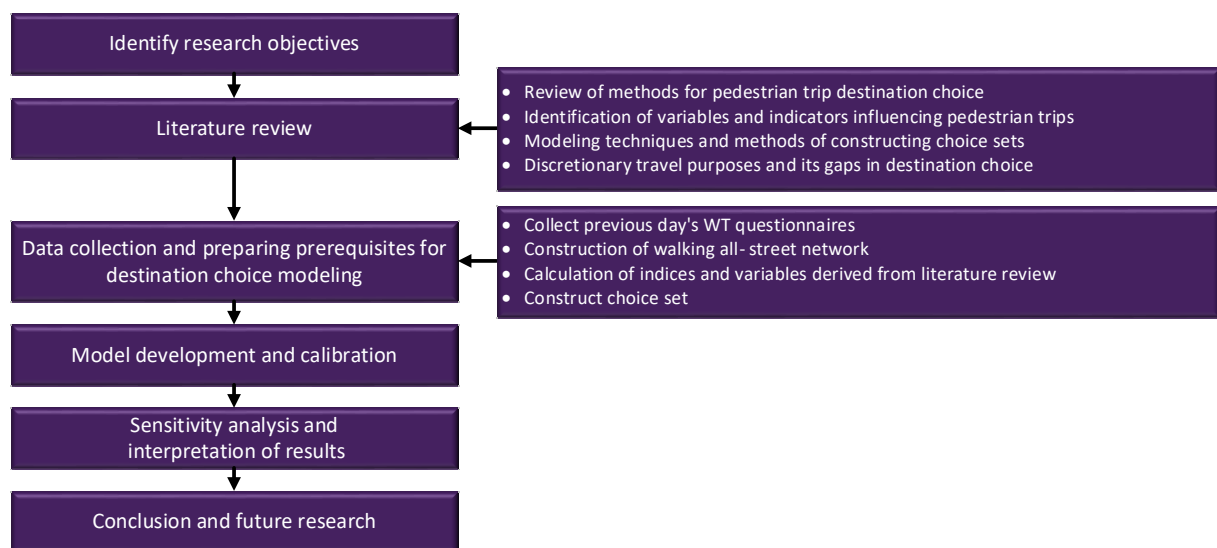


Figure 1. Research process flowchart.

3.1. Case Study

Shiraz City as a case study is the capital city of Fars Province of Iran (Figure 2), covering an area of approximately 78,800 square kilometers. According to the population estimate of 2016, it has a population of 1,683,052 people, making it the fourth most populous city in Iran in 2021 [35,36]. Shiraz City is a historical city with a history of over 1400 years [35]. It is recognized as the cultural capital and one of the most important tourist destinations in Iran with more than 150 historical, cultural, and natural attractions [37].

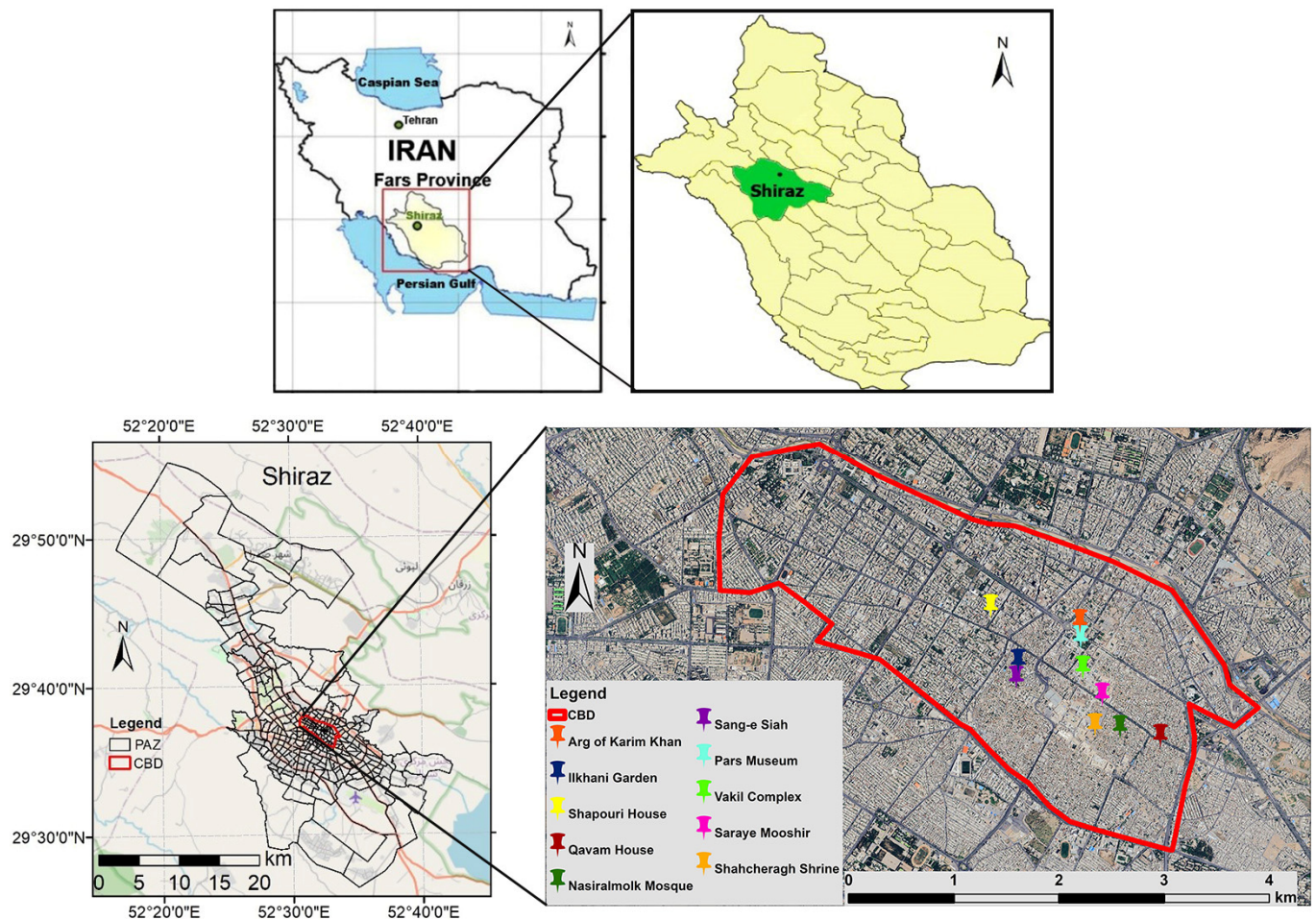


Figure 2. Location of Shiraz City on the map—CBD and non-CBD status of PAZs.

Shiraz City has a population with a tendency toward an aging population [36]. According to the origin-destination survey conducted in Shiraz City in November 2015 (about two percent sample), the average household size was found to be 3.19. Approximately 35% of the residents are employed, while the rest are homemakers, retirees, unemployed, or students. The car ownership rate in Shiraz City was reported to be around 289 vehicles per 1000 people in 2015 [38].

The non-walk trip rate for residents has been estimated at 1.81 trips per day [38], and in terms of age groups, individuals between 31 and 50 years old have the highest travel rate among other age groups. The travel rate for men is also higher than that of women [38]. According to studies on pedestrian travel modeling, more than 32% of the trips are conducted by walking as the mode of transportation [39]. Furthermore, approximately 20% of the trips have discretionary purposes [38].

3.2. Data

This paper consists of two categories of data: measurable data and data obtained from questionnaires. The first category includes data that can be measured on the street network and are calculated using GIS-based software (Visum 14). To collect these data, pedestrian facilities and pathways (such as sidewalks, pedestrian crossings, pedestrian bridges, etc.) were added to the network due to the sufficient information provided by the street network for analyzing walking trips. Connectors connect an all-streets network to pedestrian analysis zones (PAZs). The approximate area of PAZs in the city center is 15 hectares. The required data (such as LU, pedestrian walkability, travel time between PAZs, accessibility, and other variables) according to the LU for each PAZ were calculated.

The second category of data, collected through surveys, is designed to provide the necessary data for individuals' decision-making regarding their trips. After considering various methods and technological conditions, an online survey method was chosen. Although online surveys may introduce sampling, nonresponse, coverage, and demographic biases [40], efforts have been made to minimize the aforementioned errors by designing straightforward questions and conducting pilot tests. Additionally, approximately 60% of the questionnaires were collected through face-to-face interviews.

The survey questionnaire was designed to capture individuals' past-day walk trips. It was distributed among students from 87 schools in different areas of Shiraz City to collect one of their neighborhood's detailed travel data. The questionnaire allowed respondents to indicate the origin and destination of their trips on a map interface. Data collection took place from August to November of the year 2021. The data collection period was chosen to capture a range of typical travel behaviors, and at the same time, to avoid extreme weather conditions that could skew the data.

During the survey period, 4729 responses were collected, of which 1547 valid individuals responded to their past-day WTs. To enhance the model's validity, only questionnaires that were completed entirely and accurately were used. These questionnaires specifically related to WTs taken the previous day. The WT data are further divided into two categories: home-based trips and non-home-based trips. Home-based trips are categorized into three subcategories: mandatory, discretionary, and shopping trips. Among the 1547 WTs, 422 are categorized as discretionary home-based trips based on discretionary purposes, such as visiting friends and relatives, going to recreational, historical, and religious places, and so on.

3.3. Variables

In analyzing the destination choice model for discretionary home-based WTs, various variables have been examined for their effects. These variables include socio-economic variables; built and natural environmental variables; LU variables; walk indices (at the place of residence, origin, and destination of the trip); entropy; predicted travel time; educational, medical, administrative, agricultural, and military LU; the ratio of the area of these LUs to the total land area; and mixed LU variables. Some of these variables, such as the Central Business District (CBD) status of the origin zone and ownership status, are defined as dummy variables, while others, such as income level, are treated as ordinal variables. Figure 2 shows the CBD in Shiraz City.

The level of access to LU and the diversity of LU have been utilized as LU-related variables in this paper. These variables are calculated based on the indices provided in Table 1.

Table 1. Definition of indices used as independent variables in the model.

Index	Equation
Accessibility	$Accessibility_i^k = \sum_{j=1}^n \frac{Land\ use\ Area_j^k}{Ped\ Travel\ time_{ij}}$
	: accessibility to LU k in zone i, $Accessibility_i^k$: area of LU j in zone k, $Land\ use\ Area_j^k$: pedestrian travel time from zone i to j, $Ped\ Travel\ time_{ij}$ n: number of zones
	$Ped\ Travel\ time_{ij}(\text{minute}) = \frac{Ped\ distance_{ij}(\text{km})}{Ped\ Speed\left(1.2\frac{\text{m}}{\text{s}}\right)} \cdot \frac{1000}{60}$ Ped distance_{ij} represents the distance in the pedestrian network between the centroids of zones i and j. If i equals j, this distance is set equal to the root square of the area of that zone.

Table 1. Cont.

Index	Equation
Herfindahl–Hirschman index (HHI)	$HHI = P_1^2 + P_2^2 + \dots + P_m^2$ P: share of LU i (based on area), m: total number of LU types

Figure 3a demonstrates the accessibility to green spaces in 325 PAZs in Shiraz City. As seen in Figure 3a, the concentration of green spaces is higher in the central zones of the city. Figure 3b shows the accessibility to attractive LU (such as commercial, religious, tourism, cultural, sports, mixed-use, green space, protected green space, gardens and private green spaces, and residential LU in the origin zone) in PAZs.

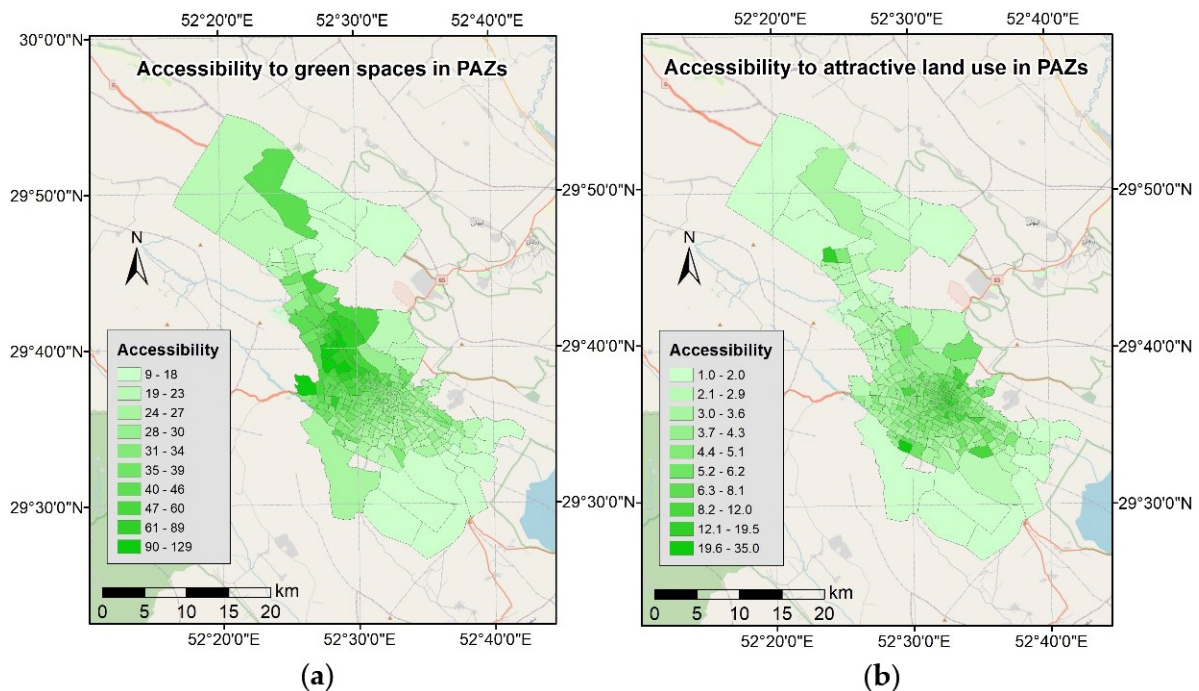


Figure 3. Accessibility to (a) green spaces and (b) attractive LU in PAZs.

The Herfindahl–Hirschman index (HHI) is another LU variable that reflects the degree of mixture of different LUs within a zone [41]. According to this equation, the higher the HHI value, the lower the LU diversity in that zone, and vice versa. In other words, if an area has only one type of LU, the HHI will be 1. Conversely, if all LU types are equally distributed, the HHI will be $1/m$ [42].

The HHI index has been calculated separately for attractive LU, Figure 4a, and unattractive LU, Figure 4b. The HHI_Atr index is used to measure the diversity of attractive LU. Similarly, to measure the diversity of unattractive LU (such as educational, administrative headquarters, healthcare, transportation and warehousing, agricultural fields, animal husbandry, military areas, industries, cemeteries, wastelands, and deteriorated areas, abandoned areas, and residential LU in the origin zone), the HHI_uAtr index is defined. The categorization of LU types as attractive and unattractive is determined based on the correlation between the destinations of discretionary trips and the density of LU. If the density of LU correlates positively with the number of attractive trips, it is considered attractive; otherwise, it is considered unattractive [38]. Table 2 presents the significant variables in the model and the descriptive statistics of these variables.

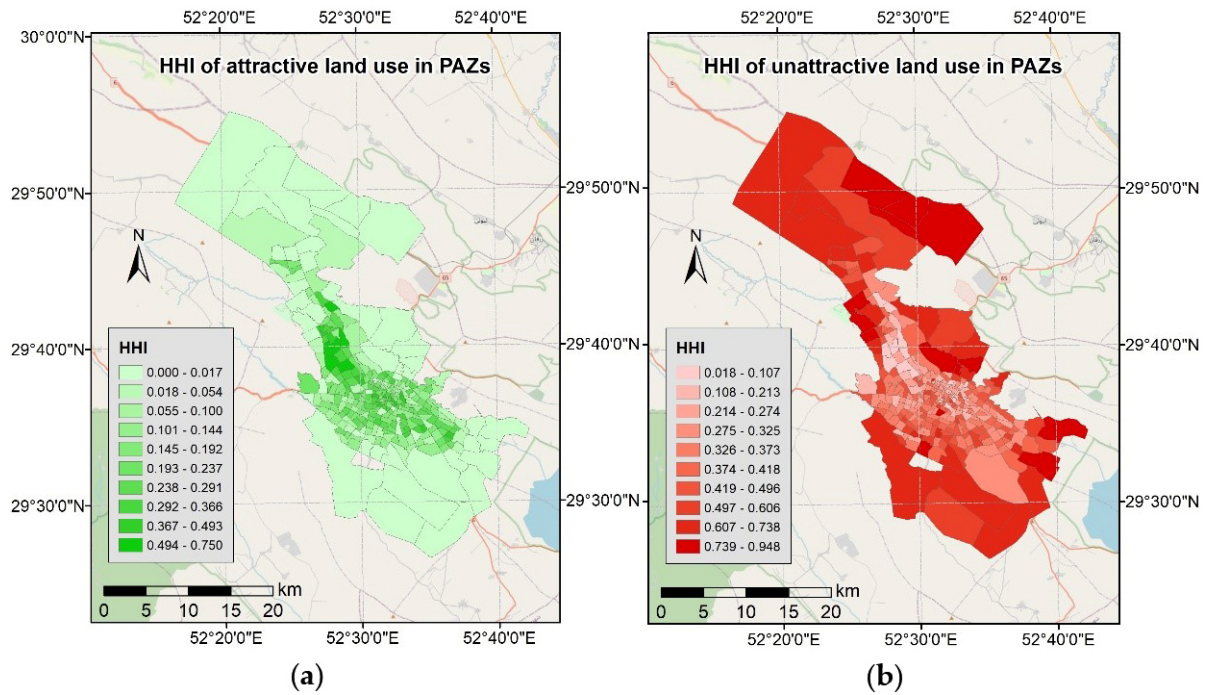


Figure 4. HHI of (a) attractive and (b) unattractive LU in PAZs.

Table 2. Variables in destination choice model for discretionary WTs.

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
HHI_Atr	The HHI of attractive LU in the origin zone	0.000	0.629	0.172	0.130
HHI_uAtr	The HHI of unattractive LU in the origin zone	0.022	0.948	0.383	0.160
CBD_i	The indicator variable represents whether the origin zone is located in the CBD	0.000	1.000	0.071	0.257
Ratio_green	The ratio of green spaces to total area (including protected green spaces, gardens, and private green spaces) in the origin zone	0.000	0.782	0.092	0.145
Acc_green	Accessibility to green spaces (including protected green spaces, gardens, and private green spaces) in the origin zone	12.558	121.182	35.806	19.836
Acc_attract	Accessibility to attractive LU (religious, tourism, cultural, and sports) in the origin zone	1.558	19.540	4.322	2.070
Pop_D_i	Population density in the origin zone	0.000	290.789	85.630	50.386
age ²	Age squared	64.000	3481.000	1101.268	699.056
H_owner	Homeownership (1 for renter, 0 for owner)	0.000	1.000	0.476	0.500

Figure 5 illustrates the status of two variables: the ratio of green space LU to the total area (a) and population density (b).

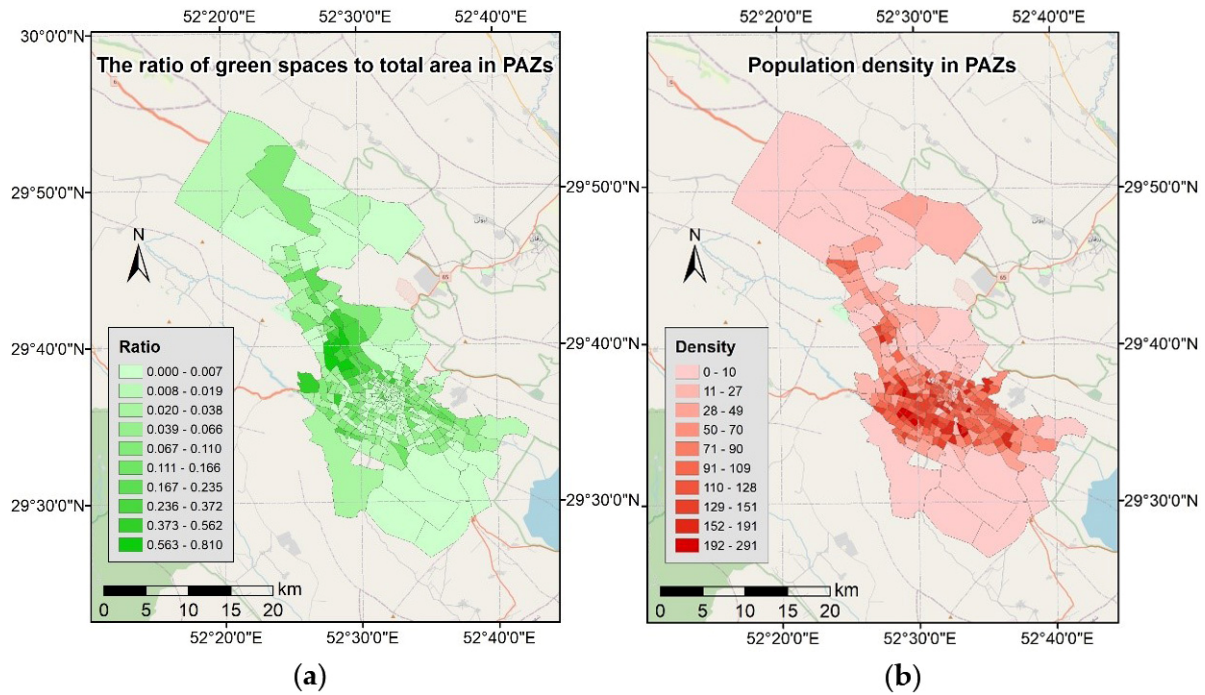


Figure 5. (a) The ratio of green spaces to total area in PAZs (b) and population density in PAZs.

3.4. Model

In the literature, various studies have widely used discrete choice models to model decision-making processes (Section 2). The probability of choosing a destination from a large set of alternatives by an individual traveling from a known origin needs to be calculated to solve the destination choice problem [14]. This paper uses a discrete choice logistic model to model the destination choice for discretionary WTs. In the logistic model, as it is not possible to consider all factors influencing an individual's choice, the utility of each alternative consists of two components: a measurable component and a random component (Equation (1)).

$$U_{ni} = V_{ni} + \epsilon_{ni} \quad (1)$$

U_{ni} : random utility of alternative i for individual n ,

V_{ni} : measurable component of destination utility,

ϵ_{ni} : random component of destination utility.

The measurable component of utility includes quantifiable attributes of individuals that can be measured, while the random component of utility captures unmeasurable factors that cannot be quantified.

In discrete choice models, different models assume different random utility distributions. The logistic model assumes that the random component of utility follows a Gumbel distribution. Additionally, the random component of utility for each alternative is assumed to have a probability distribution similar to other alternatives, and all alternatives are assumed to be independent of each other. In this case, the probability of choosing alternative i can be obtained from Equation (2) [43]:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J_n} e^{V_{nj}}} \quad (2)$$

where J_n represents the set of alternatives available to individual n .

In each experiment, only the measurable part of the utility function can be estimated. When modeling with different models, the focus is only on the measurable part of the utility function. This deterministic part is expressed as (Equation (3)):

$$V_{ni} = \beta_1 X_{ni1} + \beta_2 X_{ni2} + \dots + \beta_k X_{nik} \quad (3)$$

X : destination attributes,

β : coefficients of each attribute in the logistic regression model.

According to the provided equations and the analysis of the logistic model, it is evident that the alternatives in this model are independent of each other, which is referred to as the assumption of independent and identically distributed (IID). Based on this assumption, the introduction of a new alternative affects the probability of choosing previous alternatives (independence from irrelevant alternatives (IIA) property) [44]. This assumption is fully compatible with individuals' destination choices.

When a variable appears in the utility function for all alternatives and its coefficient is the same across all alternatives, it is called a general variable. Otherwise, it is referred to as a specific variable. Economic and social variables, as well as variables for different alternatives, should always be specified as specific variables [43]. As mentioned in this paper, variables can be categorized as population variables, economic-social variables, and LU variables. In order to assess the origin attributes in the destination choice of WTs, the variables used in the utility functions are presented as specific variables, contrary to conventional modeling approaches [18]. In other words, the variables included in the utility functions are not present in all alternatives, and their coefficients are not the same. As mentioned, this feature is one of the innovations in developing the walk destination choice model. The use of specific variables in the utility functions has increased the model's flexibility in evaluating hypotheses regarding origin characteristics in the choice of walk destinations.

3.5. Choice Sets

The large number of destination choices for each individual is one of the key challenges in destination choice modeling. The delineation of the PAZ and how to consider choice sets are crucial aspects of this challenge, and various methods have been proposed in the literature, which have been discussed in detail (Section 2). Modeling walk destination choice faces different challenges compared to other travel modes due to the shorter length of WTs. When using fine-grained zones, the number of choice alternatives increases, requiring more data to calibrate the model. In large cities, due to the limited study area, it is possible to increase the choice sets for each individual, demanding more data.

The choice set available to individual x can be assumed to be the set of PAZs $Z = \{1, \dots, n\}$, where n represents the number of PAZs. To reduce the number of destination choices for individuals, the choice set for each person has been limited to three alternatives. The first alternative (B) represents the destination within the PAZ of the origin zone. The second alternative (N) represents the destination within the PAZs adjacent to the origin zone. The third alternative (M) represents the destination outside the adjacent PAZs but within a maximum distance of 10 km. The choice sets for individuals can be written using the following notation (Equation (4)):

$$\begin{aligned} B &\subset Z \times Z, B = \{(o, d) | o, d \in Z, o = d\} \\ N &\subset Z \times Z, N = \{(o, d) | o, d \in Z, o \text{ and } d \text{ are neighbors}\} \\ M &\subset Z \times Z, \\ M &= \{(o, d) | o, d \in Z, o \text{ and } d \text{ are not neighbors}, o \neq d, Dis_{ij} < 10 \text{ km}\} \end{aligned} \quad (4)$$

After collecting the data, individual x chooses one of the alternatives. The remaining competing alternatives that the individual did not choose are defined for modeling using the following process (Equation (5)):

$$\begin{aligned}
 & \text{If } (i, j) \in B, \\
 & \text{Alternative 2 : Randomly choose a } j \text{ such that } (i, j) \in N \\
 & \text{Alternative 3 : Randomly choose a } j \text{ such that } (i, j) \in M \\
 & \text{If } (i, j) \in N, \\
 & \text{Alternative 1 : Randomly choose a } j \text{ such that } (i, j) \in B \\
 & \text{Alternative 3 : Randomly choose a } j \text{ such that } (i, j) \in M \\
 & \text{If } (i, j) \in M, \\
 & \text{Alternative 1 : Randomly choose a } j \text{ such that } (i, j) \in B \\
 & \text{Alternative 2 : Randomly choose a } j \text{ such that } (i, j) \in N
 \end{aligned} \tag{5}$$

According to these equations, two zones are randomly defined as competing alternatives. For example, suppose the selected alternative for the destination is within a certain zone. In that case, one neighboring zone of the origin zone is randomly selected as the second alternative, and another zone outside the neighboring zones within a maximum distance of 10 km from the origin zone is considered the third alternative for that individual.

This method of choosing among competing alternatives (not all) is implementable due to the IIA property. For instance, in travel mode choice models, only a small subset of the available modes can be included in the modeling process. This choice set can be applied only to discrete choice models that assume IID.

This approach to dealing with the choice set allows for modeling with a smaller number of samples, reducing data collection costs, and the distribution of a large number of questionnaires. At the same time, it enables the simultaneous evaluation of hypotheses regarding the characteristics of origin and destination in the choice of WT destinations.

4. Results

The estimated β values from Equation (3) are presented in Table 3 under the coefficient columns. In this table, the results of the multinomial logistic model for the preferences of walking trip destinations based on individual choices are presented. As mentioned in Section 3, the choice set formed for this model consists of three alternatives. Therefore, the first alternative represents the destination within the origin zone. The utility function of the second alternative corresponds to WT destinations in neighboring zones, while the utility function of the third alternative corresponds to choosing a destination outside the neighboring zones. Based on the database, among 422 discretionary WTs, 31% of individuals chose their destination within the origin zone, 24% from neighboring zones, and 45% from zones outside the neighboring areas.

Table 3. Results of the multinomial logistic regression model for discretionary home-based walking trips.

Variable	Utility 1: Walking Destination within an Intrazone		Utility 2: Walking Destination to Neighboring Zones		Utility 3: Walking Destination to Zones outside the Neighboring Zones	
	Coefficient	z Test	Coefficient	z Test	Coefficient	z Test
Constant					−0.22787	−0.49
HHI_Atr			2.55996 **	2.41		
HHI_uAtr	1.65984 ***	2.78				
CBD_i	−1.25418 *	−1.94				
Ratio_green	5.06971 ***	2.76				
Acc_green			0.02727 **	2.27	0.02947 **	2.45
Acc_attract			−0.13265 **	−2.40		
Pop_D_i					0.00922 ***	3.75
age ²					−0.00042 ***	−2.70
H_owner					0.58492 ***	2.81

Table 3. Cont.

Variable	Utility 1: Walking Destination within an Intrazone		Utility 2: Walking Destination to Neighboring Zones		Utility 3: Walking Destination to Zones outside the Neighboring Zones	
	Coefficient	z Test	Coefficient	z Test	Coefficient	z Test
Goodness of fit						
Number of observations				422		
Log-likelihood at convergence Restricted				−414.48		
Log-likelihood (constant only)				−448.72		
Log-likelihood null model				−463.61		
Akaike information criterion (AIC)				851.00		
McFadden's R^2 (ρ^2)				0.106		
ρ^2_{S}				0.076		
χ^2				98.26		
Percent correct				41.47%		

Note: *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

4.1. Model Goodness of Fit

The model goodness of fit was evaluated using various methods, including ρ^2 , ρ^2_{C} , AIC, and the chi-square test. As seen in Table 3, all the variables used in the model are statistically significant at a 10% level. McFadden's R^2 (ρ^2) value of 0.106 indicates that the fitted model is more effective and provides a better description of the population compared to the null model. It should be noted that this measure, similar to R^2 in regression models, indicates the goodness of fit but with a difference. In regression models, a higher coefficient indicates a better fit, whereas in logistic models, this coefficient is only used for model comparison purposes [43].

Another method used to assess the fitted model is the likelihood ratio test, using the chi-square distribution (χ^2). It measures the significance of the difference between the log-likelihood (LL(β)) of the fitted model and the log-likelihood (LL(0)) of the null model. A higher value compared to the critical value $\chi^2_{N,1-\alpha}$ indicates that the fitted model significantly outperforms the null model.

Another observed criterion in this table is the Akaike Information Criterion (AIC). This criterion is used to assess and select an appropriate model, indicating the amount of information lost by the model. In other words, it provides a trade-off between the number of model parameters (model complexity) and the goodness of fit to the data. Therefore, the most suitable model based on the AIC has the lowest AIC value [45].

In this model, the percentage of correctly estimated predictions is 41.47%. This value is calculated by dividing the sum of correctly estimated predictions by the total number of samples [46].

4.2. Origin and Destination Attributes

Many origin and destination attributes influencing destination choice have been examined. Significant variables are outlined in Section 3.3. Origin variables are only significant concerning pedestrian discretionary trips. This is one of the noteworthy and crucial findings of this article. The issue of which origin or destination attributes are related to the destination choice of WTs appears to be dependent on whether the trips are mandatory or non-mandatory.

4.3. Utility Function of Alternatives

Based on the utility function of the first alternative, variables such as the HHI of unattractive LU in the origin zone, the CBD status of the origin zone, and the ratio of green space to total land area in the origin zone impact the choice of destinations within the origin zone.

According to the utility function of the second alternative, variables including access to green spaces in the origin area; access to religious, tourism, cultural, and sports facilities in the origin area; and the level of attractive LU mix in the origin area affect the choice of destinations in the adjacent zones to the origin.

The utility function of the third alternative shows that variables such as access to green spaces in the origin zone, age squared, home ownership status, and population density of the origin zone also impact the choice of destinations outside the adjacent zones to the origin.

4.4. Marginal Effects of Independent Variables

Figure 6 shows the marginal effect plots of each independent variable on the probability of choosing each of the alternatives. It should be noted that the elasticity values have been calculated as arc elasticity.

The results indicate that a 1% increase in the HHI_Atr index, which represents a 1% decrease in the diversity of attractive LU in the origin zone, leads to a decrease of 0.031% in the probability of choosing a destination from within the origin zone. Additionally, the probability of choosing a destination from the adjacent zones to the origin increases by approximately 0.083%. On the other hand, a 1% increase in the HHI_uAtr index, which represents a 1% decrease in the diversity of unattractive LU in the origin zone, results in a 0.124% increase in the probability of choosing a destination from within the origin zone, a 0.050% decrease in the probability of choosing a destination from the adjacent zone, and a 0.074% decrease in the probability of choosing more distant zones.

Therefore, it can be concluded that the composition of unattractive LU in the origin zone plays a significant role in the choice of destinations for discretionary WTs. The lower the composition of unattractive LU in the origin zone, the more inclined individuals are toward choosing destinations within the origin zone, and the probability of choosing destinations closer to the origin zone increases. On the other hand, as the diversity of attractive LU in the origin zone decreases, individuals tend to choose destinations from adjacent zones. However, they show less inclination toward WTs to farther zones.

Among other LU variables, the ratio of green space area to total land area has a significant effect on the choice of destinations for such trips. Sensitivity analysis results show that a 1% increase in the ratio of green space area to total land area in the origin zone leads to a 0.100% increase in the probability of selecting destinations from within the origin zone, a 0.047% decrease in the probability of choosing destinations from neighboring zones, and a 0.053% decrease in the probability of choosing more distant zones.

Based on the defined relationship for the accessibility index, the coefficient of green space accessibility in the model indicates that with increased access to green spaces and more opportunities, individuals are more likely to choose destinations from neighboring and distant zones. On the other hand, the coefficient of accessibility to tourist, cultural, and sports facilities indicates that individuals are not inclined to choose destinations from neighboring zones to access these facilities and prefer to select their travel destinations from within the origin zone. The significance of coefficients indicates that increasing green space availability enhances the attractiveness of a zone for walk trips, while higher LU diversity makes zones with mixed residential, commercial, and recreational areas more likely to be chosen as walk trip destinations.

Another noteworthy result is that increasing population density in the origin zone decreases the probability of choosing destinations within the zone by approximately 0.090% and that of choosing neighboring zones by 0.089%, while the probability of choosing destinations from zones outside the neighboring zones increases by 0.179%. This is because high population density indicates a higher concentration of residential LU in the origin zone and less attractive amenities for WTs.

The model's statistically significant coefficient of age² indicates the quadratic relationship between destination choice and age. The results show that a 1% increase in the age² variable leads to a 0.052% increase in the probability of choosing destinations within the origin zone and a 0.046% increase in the probability of choosing neighboring zones, while the probability of choosing destinations from farther zones decreases by 0.097%. In other words, older people are more likely to choose closer destinations, whereas younger people are more likely to choose more distant destinations.

The sensitivity analysis of the homeownership status variable, which is considered an economic factor, indicates that individuals who are renters have a greater tendency to make WTs to farther zones. Assuming that all individuals are tenants, the probability of choosing alternative three increases by 12.755%, followed by a decrease of 6.82% and 5.935% in the probability of choosing alternative one and two, respectively, compared to the scenario where no one is a tenant.

Another considerable dummy variable is the residential location variable within the CBD. If the origin of individuals' trips is within the CBD, the probability of intra-zone trips decreases, while the likelihood of choosing destinations from adjacent and farther areas increases. Assuming all origin zones are CBD, the probability of choosing alternative one decreases by 19.322%, followed by an increase of 7.778% and 11.546% in the probability of choosing alternatives two and three, respectively, compared to the scenario where no zone is CBD. This variable behaves similarly to accessibility to green spaces.

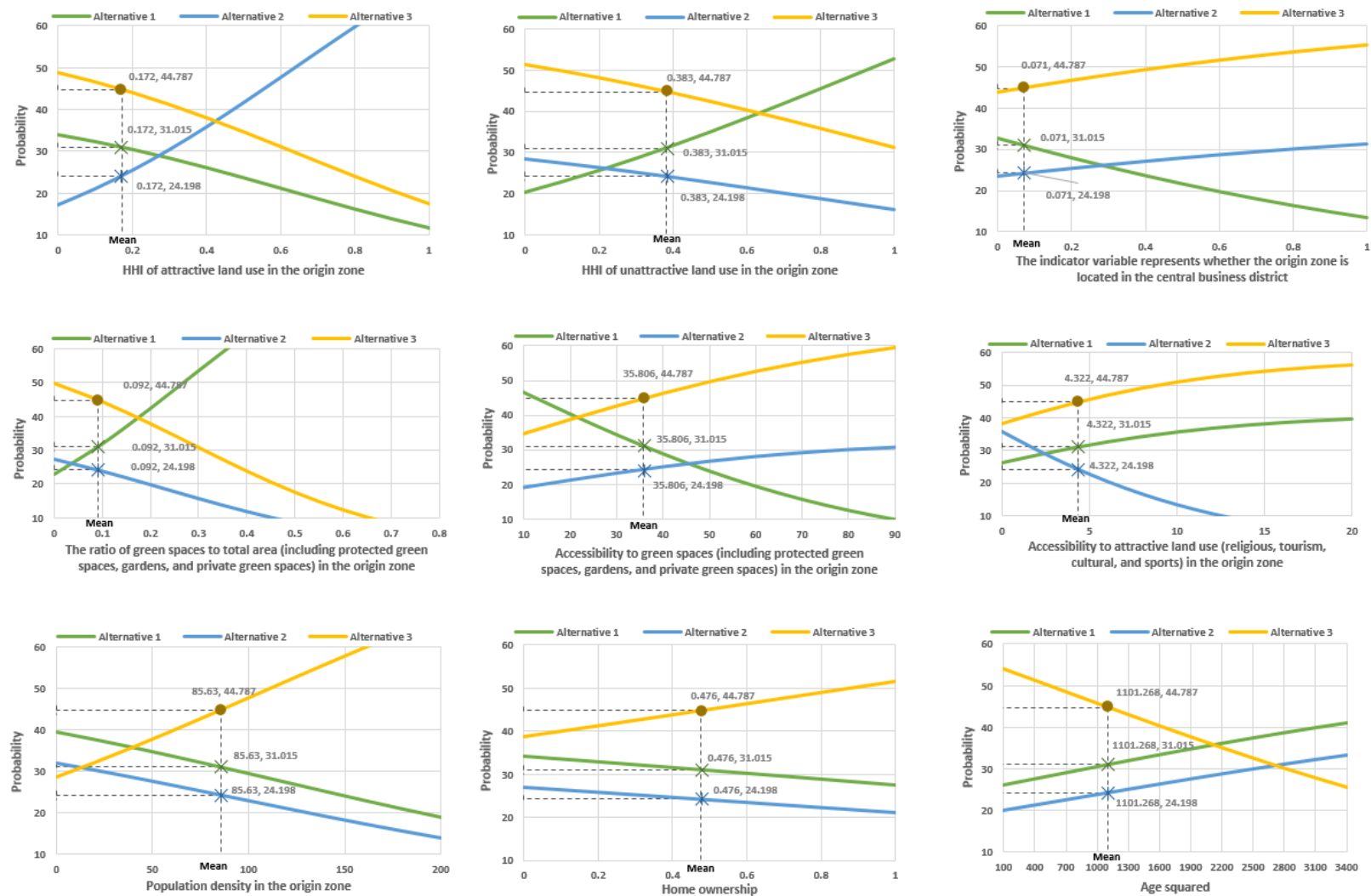


Figure 6. Marginal effect plots of independent variables in the model.

5. Discussion

This study extends previous findings on the application of destination choice models by demonstrating its effectiveness in pedestrian travel demand estimation, leading to more accurate planning for this mode [9]. These findings can be integrated with other travel demand models to simulate pedestrian trips and improve walkability through network and land-use adjustments. Additionally, the identification of policy-related variables (e.g., land-use variables, accessibility, HHI) that significantly influence discretionary trips offers valuable insights for policymakers to design incentive-based programs rather than restrictive policies, which are not suitable for such trips.

Traditionally, destination choice models have focused primarily on characteristics of the destinations themselves and trip features. This study breaks new ground by revealing that factors specific to the origin also play a crucial role in shaping pedestrian destination choices. This finding can significantly improve travel demand modeling and inform policies to promote walking.

5.1. Land Use

Among the LU variables, it is observed that the index of diversity in unattractive LU has a notable impact on the destination choice of discretionary WTs compared to the index of diversity in attractive LU. In other words, individuals show a greater inclination toward WTs within the zone when the diversity of unattractive LU is lower. The appropriate combination of LUs plays a crucial role in increasing recreational WTs as well as daily WTs [47]. In similar research, the variable of LU combination (residential, commercial, public, and industrial) and the index of dissimilar LUs were used in modeling the destination choice of WTs. The greater difference in LU implied a more attractive destination. The results indicated that the combination of LUs had a positive effect on the choice of non-motorized trips, and the index of dissimilar LUs had a positive effect on the choice of motorized trips. It is not only the quantity of LUs but also the quality and type of services they offer that significantly influence the choice of non-motorized trips [48]. The results of modeling in another research indicate that mixed LU (residential, commercial, administrative, industrial, and recreational) has a positive effect on the distance covered in WTs, which contradicts the findings of the current research [25]. It is observed that mixed LU, in a way that promotes proximity to non-residential LU (commercial, office, and recreational centers), facilitates shorter trips and reduces the need for motorized transportation [49]. It should be noted that these studies did not differentiate between attractive and unattractive LU in terms of their combinations.

5.2. Green Spaces

The significant area of green space in the origin area increases people's inclination to choose their destination from the same origin. Green spaces not only provide natural landscapes but also enhance the environment through beautification, air purification, reduction of noise pollution, and shade, which attract WTs [50]. Previous studies have also found a positive correlation between WTs and green spaces [51,52]. The model developed demonstrates that the contribution of green space has a significant positive impact on walking and bicycle trips [52]. The results of a recently conducted study are consistent with the findings of the present research. However, in some other studies, no relationship between green spaces and recreational WTs has been observed [53]. The modeling results of another study in Spain show that increased access to green spaces leads to an increase in walking. This variable has a greater influence in urban zones compared to rural zones [54].

5.3. CBD Location

The location of the trip's origins in the CBD is another influential factor in such WTs. Studies have shown that due to smaller divisions in these zones, the trips made to neighboring and distant zones are more frequent, and the distances covered are significantly shorter than WTs originating from non-CBD zones. Analyzing the walk travel database

in Shiraz City reveals that the average length of WTs originating from non-CBD zones is approximately four times longer than those starting from CBD zones. Therefore, individuals whose WTs originate in CBD zones tend to cover shorter distances despite making more trips to zones outside the origin zone. The reason for this could be attributed to the presence of more opportunities in CBD zones or the smaller subdivisions and smaller zones in the CBD. Some previous studies have also obtained similar results. These studies have shown that the average block size has a negative impact on walk travel choices. Larger blocks act as barriers to WTs, while smaller blocks and a higher number of intersections provide more routes for accessing destinations, encouraging individuals to choose WTs [25,55].

5.4. Non-Policy-Related Variables

Higher population density in the origin zone correlates with traveling to farther zones for discretionary walk trips, emphasizing the role of LU planning. Consistent with recent studies, residential density positively influences travel distance rather than mode choice [25]. However, results vary across studies due to different trip objectives and methodological approaches [53,54,56].

The age variable shows that younger and older individuals prefer closer destinations for walking trips, avoiding distant zones. Previous studies highlight that different age groups, especially children and the elderly, exhibit distinct behaviors [12,24,57]. Older adults are more sensitive to travel time and value green spaces, while younger individuals consider travel distance and commercial centers [58].

Studies show renters walk longer distances for discretionary trips due to lower car ownership compared to homeowners. The investigations carried out on the walk travel database in Shiraz City show that 52% of respondents were renters with a car ownership rate of 0.86 per household, while homeowners had a rate of 1.12. Renters prefer walking more for discretionary trips. Car ownership and house size are significant economic indicators.

5.5. Limitations

The researchers acknowledge the limitations of potential aggregation bias and take steps to mitigate these limitations by randomly assigning zones to alternative destinations, thereby controlling for confounding variables that might otherwise influence the results.

The application of this research is to model destination choice with some limitations. The purpose is to create a tool for planning and identifying policy-related variables at the regional level to improve the distribution of trips within cities. Using predictable variables and aggregating LU data at the zone level are positive aspects of this research. However, at the individual level, some personal attitudes and latent variables are not considered due to their unpredictability. Additionally, the focus on modeling destination choice assumes that individuals' decisions regarding trip generation, mode choice, and route choice do not influence destination choice.

It is worth mentioning that the collected data are cross-sectional and do not allow for examining the impact of LU changes over time. For future studies, the model results should be compared for more periods to assess the effect of LU changes on walk destination choice.

6. Conclusions and Suggestions

In recent years, there has been a shift in transportation planning approaches from car-oriented to active modes, which has led to the increased importance of modeling WTs. Given the novelty of walk destination choice and the lack of research in this area, there is a need to identify the influential variables. The current paper aims to develop destination choice models for discretionary home-based WTs. A discrete choice logit model has been applied to model the discretionary home-based WTs in Shiraz City as a case study. The use of policy-sensitive variables in the model, the variables employed in utility functions, and the consideration of choice sets are among the innovations of this research.

The results of the model indicate that LU variables such as LU diversity (differentiating between attractive and unattractive LU), residential LU density, green space area, and

recreational, cultural, and sports facilities have an impact on the destination choice for discretionary home-based WT. Urban design and planning should avoid increasing residential block density, as this can lead to longer trips and greater reliance on motorized transportation. On the other hand, increasing the diversity of attractive LU and green spaces in zones encourages individuals to engage in WTs. It is noteworthy that reducing the diversity of unattractive LU compared to increasing the diversity of attractive LU has a more significant impact on the destination choice for discretionary home-based WTs.

The analysis of pedestrian travel data in Shiraz City shows that trips starting from non-CBD zones are about four times longer on average compared to those originating from the CBD zones. Individuals beginning their trips in CBD areas tend to cover shorter distances despite making more trips to zones outside the CBD. The possible reasons for this behavior could be the availability of more opportunities in CBD zones.

Another notable finding is that the age-dependent behavior of the age variable indicates different pedestrian travel behaviors in older age groups compared to other individuals. The aging population in Shiraz City creates specific conditions for future pedestrian behavior. The examination of the pedestrian travel database in Shiraz City reveals that individuals classified as renters exhibit a greater inclination towards choosing walking as their preferred mode of transportation for discretionary trips in comparison to homeowners.

Based on the literature review, it has been shown that current models for pedestrian trip demand are sensitive to destination characteristics but do not consider origin characteristics. This paper argues that there is a need to revise these models to take into account origin characteristics as well. Although this study observed that the origin characteristics influence discretionary trips, their effects on destination choice for mandatory trips remain unknown. Therefore, this hypothesis should be evaluated for other trip purposes as well.

Considering that destination choice models are also used to predict future destination choices in travel demand models, it is recommended to collect data over several periods and identify variables that ensure temporal stability to incorporate them into the models.

The results can be utilized in urban LU distribution and future urban planning for walk activities. Although the proposed method is general and can be applied to other cities, a spatial feasibility study to assess the sensitivity of the variables is recommended.

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