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Which Neighborhood Matters? Estimating Multiple-Location Built Environment Effects on the Modality Style

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Abstract: The literature on the built environment (BE) and travel has offered evidence on both short- and long-term aspects of travel behavior with a main focus on home and work neighborhoods; however, the effects of the BE at the main activity space on the modality style have remained largely unknown. Moreover, little is known about the inter-modal substitutions and how the substitution is affected by the satiation effects. Based on survey data from Beijing, a Multiple Discrete Continuous Extreme Value (MDCEV) model is adopted to reveal the effects of BE at home, work, and activity space locations on the modality style. Results show that BE features at the home, work, and main activity space neighborhoods are essential triggers of the modality style, among which home BE features play the most vital role. The satiation effects visualized from various travel modes suggest that car traveling remains the most preferred travel mode. These findings can provide refined BE planning implications according to local land-use patterns for urban planners and transport policymakers because a one-size-fits-all design is not a solution to regulate people's travel behavior.

Keywords: built environment; multiple location; modality style; multiple discrete continuous extreme value model; China

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1. Introduction

In recent decades, many developing countries have experienced rapid growth in using cars as a dominant pattern of trips in urban areas. For instance, in 2022, the number of private cars in China exceeded 301.51 million. Car dependence is an important factor in traffic congestion, environmental issues, and the obesity epidemic. Moreover, car dependence is still growing rapidly in developing countries like China. Owing to the negative effects of car use on the environment and society, researchers and practitioners are seeking solutions to address these concerns. On the other hand, the Chinese context where car dependence has rapidly increased provides a good opportunity for observing travel behavior and its determinants.

In the literature, factors from various perspectives are explored (e.g., such as urban planning and transport policymaking), among which the surrounding built environment (BE) plays a major role in shaping individual travel patterns [1–5]. To provide more refined planning strategies, researchers have recently begun to extend the spatial locations from home neighborhoods to work and activity space neighborhoods [6–9]. This stream of research on multiple-location BE mainly focuses on the short-term aspects of travelers' mode choice behavior, i.e., one specific trip. However, significant gaps are yet to be bridged regarding the longer-term aspects of travel behavior, such as the modality style, which is

characterized by a specific mode or a set of modes that an individual frequently uses [10]. Considering that the main activity space locations predominantly affect individual travel decisions [11], it is of significance to re-examine the importance of the BE at the main activity when exploring the effects of the BE on the modality style.

More importantly, people tend to generate daily trips by at least three main modes: active modes, public transit, and car; measures of travel behavior by each mode may be interrelated [12]. For instance, given that a person tends to have a fixed number of activities within a specific time quantum, more frequent usage of one mode may hinder the usage of other modes. However, previous research tends to ignore the above inter-modal substitutions and how the substitution is affected by the satiation effects. The literature primarily focuses on the variables affecting the frequency of each mode as an isolated mode of transport and assumes independent errors across various modes [13]. Such an assumption may produce biased estimations.

To bridge the above gaps, we seek to employ the Multiple Discrete Continuous Extreme Value (MDCEV), which can effectively capture the satiation effects from different modes, to explore the effects of BE features at three locations (i.e., home, work, and main activity space) on the modal style based on survey data from China, Beijing. This study can enrich the current knowledge by answering the following questions: (1) Which one of the home, work, and activity space neighborhoods matters for the modal style? (2) What aspects of BE features have significant effects on the modal style? (3) Whether the satiation effects from different modes exist?

This paper is organized as follows. Section 2 presents a review of related research. Section 3 describes the data and approach of this study. Section 4 describes the estimation results. The final Section presents the key findings and limitations of this study.

2. Literature Review

A large body of research has investigated the link between BE and travel behavior from various perspectives [14–16]. In terms of the study of Ewing and Cervero, the BE is characterized by density, design, diversity, destination accessibility, and distance to transit, which are accepted as the "5Ds" [17,18]. Regarding travel behavior, the BE and travel literature have focused on different aspects of travel behavior, varying from travel time [19], travel distance [20], vehicle miles traveled [21], and transit ridership [3], to mode choice [9]. Most of the literature suggests that the D variables significantly affect travel behavior. For instance, Wang et al. employed a hierarchical cross-classified structural equation model to explore the effects of the BE on commuting mode choice and found most BE variables are significant factors [9]. In another example, Sun et al. analyzed survey data from Shanghai and found that BE features are factors of commuting mode choice and commuting distance [20]. Apart from these short-term aspects of travel behavior, concrete evidence supporting the importance of considering longer-term travel and lifestyle choices (e.g., car ownership and the modality style) can also be found in the BE and travel literature [13,14,22,23]. The modality style, defined as a set of frequent travel modes characterizing the travelers' habits, routines, and predispositions [10], plays an essential role in forming the dynamics of travelers' mode choice behavior. Thus, understanding the effects of BE on the modality style is important for encouraging sustainable travel behavior.

The BE–travel literature has primarily paid attention to BE features at home neighborhoods [24–28]. For example, Wang et al. analyzed survey data from 97 Chinese cities and found that residential BE features significantly affect commuting duration [19]. Ding et al. analyzed household travel data in Beijing and explored the relationships between residential BE attributes and commuting by transit [2]. Wu et al. employed two-step clustering and gradient-boosted regression trees to explore the effects of residential BE features on the

commuting time of active commuters based on survey data from Nanjing [17]. The findings suggest that there is spatial heterogeneity in their relationships, and most BE features show significant effects on the commuting time of active commuters after accounting for the spatial heterogeneity [13]. The findings show that most BE features show nonlinear effects on housing renters' transit commuting. This stream of research only describes part of the story as BE features at multiple out-of-home locations (e.g., trip destinations) also play an essential role in shaping travel behavior [29].

Some recent studies have identified several typical out-of-home BE contexts, such as work locations [6], mid-stop locations [30], and main activity locations [7,31]. Although the effect sizes of home and out-of-home BE features are debatable [20,32], the literature has reached a consensus on their essential roles in affecting travel behavior. For example, Zhang found that BE features at home neighborhoods and trip destinations play an essential role in affecting mode choice [29]. Moreover, BE features at trip destinations have greater effects than those at home neighborhoods. Based on survey data from Oregon, Fang et al. also found that BE features at main activity locations play a more essential role in affecting mode choice [7]. In another example, Sun et al. found that home BE features are more influential on commuting outcomes than BE features at work locations by analyzing survey data from Shanghai [20]. Overlooking these important out-of-home BE contexts may lead to biased estimations and provide misleading policy implications. Thus, it is necessary to include both home and out-of-home BE features, especially for long-term travel behavior, which usually involves multiple out-of-home locations.

Most earlier studies analyze individuals' travel behavior by each mode (e.g., trip length and trip frequency) as an isolated transport mode [33–36]. For example, Larrañaga et al. found that BE features at home neighborhoods, including population density, intersection density, and service density, are essential triggers of the frequency of daily walking trips [34]. Based on two-stage hurdle models, Park et al. analyzed the BE features at home neighborhoods and the number of car trips, transit trips, and walk trips, and found that most BE features have significant effects on trip generation [35]. However, it is argued that travel behavior by each mode should be correlated with each other rather than independent. The assumption that error terms are dependent across equations may lead to biased estimation results and inappropriate planning practices. For instance, given a fixed number of activities, frequent usage of one specific mode may prevent the usage of other modes [12]. From another point of view, travel time savings, caused by faster speed, declined distance, or other reasons, may lead to additional demand by other modes in turn [37]. In addition, some unobserved terms (e.g., affinity or disaffinity for travel) can simultaneously affect the usage of different modes. To address the correlations among different measures of travel behavior, seemingly unrelated regressions have been widely used to model trip generation [14,38,39]. For instance, Cao et al. applied a seemingly unrelated regression approach to analyze the effects of BE features on modality style and confirmed that there exists a correlation among the trip frequencies by car, transit, and active modes [14]. In another example, Gao et al. explored the effects of residential consonance and dissonance on travel behavior based on data from the Netherlands [38]. The estimation results of the seemingly unrelated regression suggest the importance of incorporating the correlations between travel frequencies of household couples. An essential limitation in this stream of research is that researchers usually ignore the inter-modal substitutions and how the substitution is affected by the satiation effects [13]. Traditional models, such as seemingly unrelated regressions, hurdle models, and Poisson models, cannot address these issues. The multiple discrete–continuous choice models provide a solution to this question. However, an analysis of BE features at multiple locations and trip frequency by each mode remains scant.

In summary, although the literature has provided evidence on the BE features and travel behavior from various perspectives, the role of BE features at out-of-home locations is usually overlooked [7]. Understanding the effects of BE features is essential for making refined planning efforts. Moreover, the inter-modal substitutions and how the substitution is affected by the satiation effects when modeling travel behavior by different modes remain largely unknown. In this paper, we seek to bridge these gaps by adopting the MDCEV approach to explore the effects of BE features at home, main activity, and work neighborhoods, and identify the inter-modal substitutions.

3. Methodology

3.1. Data

To estimate multiple-location BE effects on the modality style, data collected from an online travel survey conducted by the authors in Beijing from September 2018 to February 2019 were analyzed. A stratified random sampling approach was used in neighborhoods covering central urban regions, suburban regions, and outer suburb regions (see Figure 1). A major Internet survey firm in China, namely, Sojump, which has more than 6.2 million registered users, helped us conduct the survey. We used a stratified random sampling method to ensure the representative of the sample according to the population in each region. After determining the number of respondents in three types of regions, the respondents were randomly selected in each region. We collected the questionnaires through an online interview. In the process, the authors checked the answers and asked for feedback on some questions. Those whose questionnaires passed the check were paid RMB 15. As a result, 1024 valid questionnaires were finally obtained. According to gender and geographic distribution, the sample distribution was in accordance with the whole population in Beijing (see Table 1).

Table 1. Sample distribution.

Variable	Description	Census of Beijing		Sample	
		N (Million Persons)	%	N (Person)	%
Gender	Man	11.07	51.02%	517	49.90%
	Woman	10.63	48.98%	519	50.10%
Geographic distribution	Central urban region	2.07	9.54%	105	10.14%
	Suburban region	10.02	46.15%	451	43.53%
	Outer suburb region	9.62	44.31%	480	46.33%
	Sum	21.71	100.00%	1036	100.00%

The focus of this study is on the factors of the modality style. Three modes, including active modes, public transit, and car, were used for this analysis. The frequency of using each mode within a one-week period was treated as the dependent variable. Such a long-time travel cycle can reflect the modality style and be used for the analysis of their inter-modal substitutions and how the substitution is affected by the satiation effects. Table 2 depicts the distribution of the usage frequencies. As individual features are important factors of travel frequency, nine factors, including gender, age, income, education, household size, child, elderly, car ownership, and driving license, are considered in this study. The individual features are recorded in the survey.

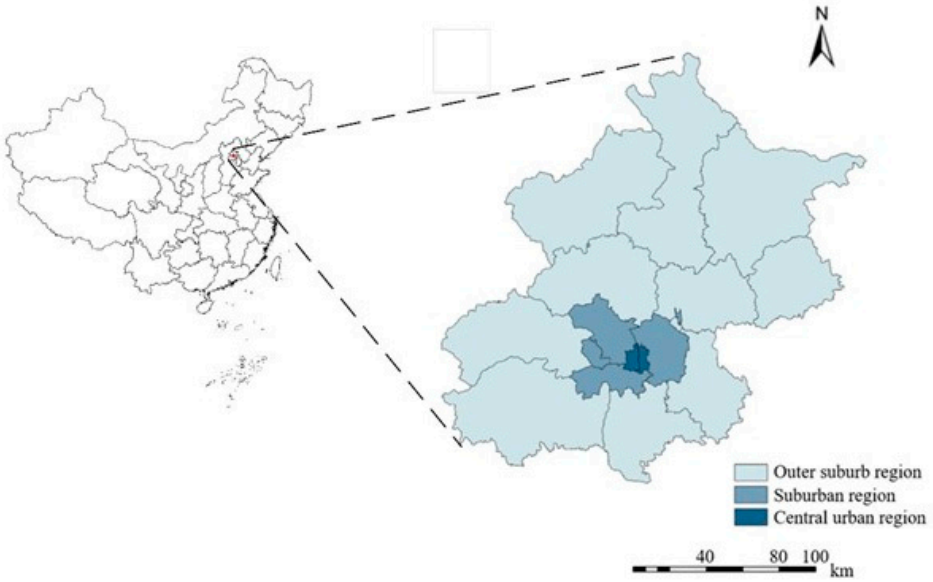


Figure 1. Study area.

Table 2. Statistical characteristics of individual variables.

Factor	Description	Mean	St. Dev.
	Dependent variables		
Any active trips	Any active trips (1: yes; 0: no)	0.89	0.31
Active trips	Number of active trips within a week	7.27	10.75
Any transit trips	Any transit trips (1: yes; 0: no)	0.84	0.34
Transit trips	Number of transit trips within a week	5.40	16.49
Any car trips	Any car trips (1: yes; 0: no)	0.73	0.44
Car trips	Number of car trips within a week	3.40	6.05
	Individual features		
Gender	Male (1: yes; 0: no)	0.50	0.50
Age	Years old	33.87	9.50
Income	Personal monthly income: 1 = below RMB 3000; 2 = between RMB 3001 and 4500; 3 = between RMB 4501 and 6000; 4 = between RMB 6001 and 8000; 5 = between RMB 8001 and 10,000; 6 = between RMB 10,001 and 15,000; 7 = higher than RMB 15,000	4.31	1.83
Education	Have a college diploma (1: yes; 0: no)	0.78	0.41
Household size	Number of persons in the household	2.89	1.33
Child	Have a primary school student (1: yes; 0: no)	0.42	0.60
Elderly	Have an elderly more than sixty years old (1: yes; 0: no)	0.41	0.77
Car ownership	Own a car (1: yes; 0: no)	0.72	0.45
Driving license	Number of driving licenses in the household	1.98	0.91

The respondents were asked to report the locations of their home, work, and main activity space. Based on the location information, BE features were extracted from multiple sources, as shown in Table 3. The variable of residential density was extracted from the LandScan population dataset (see https://landscan.ornl.gov for details). In the dataset, cities were segmented into same-size square grids, and residential density in each grid was provided, and 1 km buffers were used as the spatial unit of bus stop density, land-use mix, and road network density. Road network density was calculated based on the ratio of the road lengths to the buffer area. The road lengths were extracted from the open street

map. The variables of distance to city center, distance to district center, bus stop density, and land-use mix were calculated according to points of interest (POIs) and were provided by AMAP.com, which is the largest provider of navigation and location services in China. The entropy approach was used to calculate the value of the land-use mix based on eight categories of POIs (i.e., plazas, companies, hotels, restaurants, schools, hospitals, banks, and governments) as follows [40]:

$$E = \frac{-\sum_{i=1}^{s} p_i \ln(p_i)}{\ln s} \quad (1)$$

where p_i denotes the ratio of i th category of POIs. s is the number of the category of POIs.

Table 3. Statistical characteristics of BE variables.

Factor	Description	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Home built environment							
Land-use mix	A measurement of different POIs based on the entropy approach	0.58	0.16	0.61	0.19	0.44	0.10
Bus stop density	Number of bus stops/buffer areas (/km^2)	12.34	8.23	15.63	10.08	10.48	6.35
Road network density	Road lengths/buffer areas (km/km^2)	46.17	54.25	47.32	55.02	40.33	50.27
Distance to local center	Distance from home to district center (km)	6.63	6.81	6.21	6.45	6.54	6.79
Distance to city center	Distance from home to city center (km)	22.73	19.01	20.13	18.65	20.14	17.08
Residential density	Population size/neighborhood area in the residential grid (thousand persons/km^2)	36.04	28.87	26.45	24.19	25.01	18.85

3.2. MDCEV Model

The MDCEV model was applied to estimate the impacts of BE features on the modality style. The framework of the MDCEV model is shown in Figure 2.

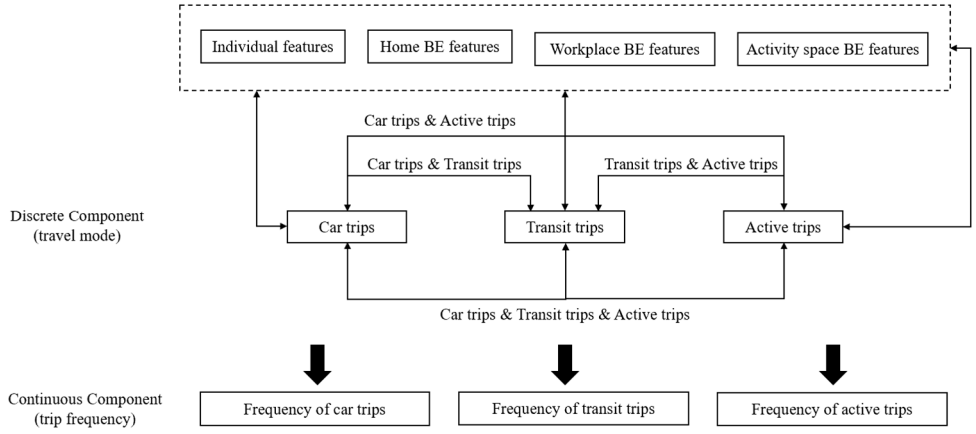


Figure 2. Framework of the MDCEV.

The MDCEV model is a KT-based method, in which all consumers' consumption quantities are constrained in terms of their budgets B [41]. To better understand the constraint, it was assumed that a consumer allocates his or her budget to several options $k \in \{1, 2, \ldots, K\}$. Thus, the budget constraint is represented as follows:

$$\sum_{k=1}^{K} e_k = B \quad (2)$$

where $e_k = p_k C_k \forall k$. p_k is a parameter that transforms the consumption quantity C_k to expenditure e_k, which shows the same unit as B. In this study, the consumption quantity and budget have the same unit: travel frequency. Thus, $p_k = 1$ is set for all k.

The overall utility derived from consuming C_k units of options $k = 1, 2, \ldots, K$, represented by Equation (3).

$$U(C) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \varphi_k \left(\left(\frac{C_k}{\gamma_k} \right)^{\alpha_k} - 1 \right) \tag{3}$$

where α_k and γ_k are the satiation parameter and translation parameter, respectively. α_k describes the diminishing marginal utility of consuming k. Different values of α_k indicate different relationship patterns between options. When $\alpha_k = 1$, the satiation effect is the lowest, indicating a linear competitive relationship between option k and other options. The satiation effect for option k increases with α_k decreasing from 1. γ_k has two main functions, which have been well documented in the study of Bhat [41]. First, it prevents indifference curves from becoming asymptotic to axes in the positive orthant. Second, it composes a satiation profile with α_k. A value of γ_k closer to 0 indicates a higher rate of diminishing marginal utility for a given level of the baseline preference.

φ_k represents the baseline preference for option k. The parameter φ_k can be explained by the marginal utility for option k before using it for the very first time during the week (i.e., $C_k = 0$). The parameter φ_k can be represented as follows:

$$\varphi_k = \exp(\beta_k Z_k + \varepsilon_k) \tag{4}$$

where Z_k represents independent variables and β_k represents corresponding parameters. ε_k is the error term for capturing the effect of unobserved predictors on the baseline utility φ_k.

Owing to the difficulty in simultaneously estimating α_k and γ_k in the MDCEV model. Usually, three types of utility forms are estimated as follows:

$$U(C) = \sum_{k=1}^{K} \frac{1}{\alpha_k} \varphi_k \left((C_k)^{\alpha_k} - 1 \right) \tag{5}$$

$$U(C) = \sum_{k=1}^{K} \gamma_k \varphi_k \ln \left(\frac{C_k}{\gamma_k} - 1 \right) \tag{6}$$

$$U(C) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha} \varphi_k \left(\left(\frac{C_k}{\gamma_k} \right)^{\alpha} - 1 \right) \tag{7}$$

where Equation (5) is referred to as the MDCEV model with α-profile, in which all γ_k are equal to 1. In this profile, the model represents the diminishing marginal utility with the consumption increasing and assumes a different performance of satiation for different options. Equation (6) is referred to as the MDCEV model with γ-profile, in which we set $\alpha \to 0$. In this profile, the model exhibits a logarithmic utility structure. Equation (7) is referred to as the MDCEV model with constant α profile, which simply combines α-profile and γ-profile.

It is assumed that every traveler maximizes the total utility by using various options, given his/her budget. Based on the Kuhn–Tucker (KT) conditions, the probability that the optimal expenditures are chosen can be represented as follows:

$$P(e_1^*, e_2^*, \ldots, e_M^*, 0, \ldots, 0) = \frac{1}{\sigma^{M-1}} \left[\prod_{i=1}^{M} \varsigma_i\right] \left[\sum_{i=1}^{M} \frac{1}{\varsigma_i}\right] \left[\frac{\prod_{i=1}^{M} \exp(V_i/\sigma)}{\left(\sum_{k=1}^{K} \exp(V_k/\sigma)\right)^M}\right] (M-1)! \quad (8)$$

where the set $e^* = \{e_1^*, e_2^*, \ldots, e_M^*, 0, \ldots, 0\}$ represents the optimal expenditure of a traveler, where $i = 1, 2, \ldots, K$. It is assumed that the first M options are used ($M \leq K$) and the rest are not used ($e_1^* > 0 \; \forall \; i > M$).

4. Results

4.1. Model Performance

Three MDCEV models, namely, α-profile, γ-profile, and constant α profile, are estimated in this study. The estimated results of the above models show that the model with γ-profile (log-likelihood: −14,256.45) performs better than the α-profile (log-likelihood: −15,278.31) and constant α profile (log-likelihood: −14,297.82). A larger log-likelihood value means better model performance. Thus, the estimated results of the MDCEV model with γ-profile are discussed in the rest of this Section.

4.2. Features Influencing Modality Style

The estimation results of the MDCEV model with γ-profile are shown in Table 4. The results show that the γ value of car trips is the smallest among the three types of trips, suggesting that car trips have a higher rate of diminishing marginal utility for a certain level of the baseline preference. The baseline utility in MDCEV models refers to the marginal utility of a certain mode at the point of zero consumption.

Table 4. Model results.

Variable	Active Modes		Public Transit		Car	
	Est	S.E.	Est	S.E.	Est	S.E.
γ	87.325 **	0.872	20.458 **	0.975	3.408 *	1.890
Individual features						
Gender	−0.116	0.068	−0.063	0.105	0.138	0.079
Age	0.011 **	0.003	−0.022 *	0.013	0.019 **	0.008
Education	0.072	0.088	−0.131 *	0.075	0.101 **	0.047
Income	0.036 *	0.021	−0.027 *	0.014	0.258 **	0.116
Driver license	−0.147	0.245	−0.035	0.024	0.325 **	0.081
Car ownership	−0.302 **	0.118	−0.203 **	0.103	0.439 **	0.081
Household size	0.107	0.132	−0.211 **	0.008	0.127 **	0.004
Household with children	−0.060	0.070	−0.054 **	0.021	0.073 *	0.038
Household with elderly	−0.026	0.054	−0.010	0.083	0.013 *	0.007
Home BE features						
Entropy	0.122 **	0.038	0.118 *	0.066	−0.219 **	0.076
Stop density	−0.031	0.058	0.074 **	0.032	−0.058 *	0.032
Road density	0.003 **	0.001	0.026 *	0.014	−0.005 **	0.003
Distance to city center	−0.031	0.035	−0.017 **	0.006	0.028 *	0.015
Population density	0.026 *	0.015	0.024 **	0.010	−0.008 **	0.004
Workplace BE features						
Entropy	0.068 *	0.031	0.014	0.012	−0.112 **	0.043
Stop density	−0.101	0.079	0.062	0.075	−0.032	0.024
Road density	0.005	0.009	0.058 **	0.014	−0.005	0.005
Distance to city center	0.023	0.035	−0.019	0.054	0.056	0.049
Population density	0.007	0.017	0.045 *	0.027	−0.012	0.010
Activity space BE features						
Entropy	0.097 **	0.028	0.085	0.078	−0.154 **	0.071
Stop density	−0.050	0.057	0.109 *	0.051	−0.038	0.031
Road density	0.005	0.014	0.035 **	0.017	−0.005	0.005
Distance to city center	−0.010	0.024	−0.035	0.037	0.016 *	0.009
Population density	0.005 *	0.003	0.095 **	0.026	−0.020 **	0.009
Number of observations	1036					
Log-likelihood	−14,256.45					

* $p < 0.1$, ** $p < 0.05$.

Among individual features, most factors are significantly influential on the modality style. Older residents have a higher tendency toward traveling by active modes and car but use public transit less frequently. Well-educated residents are inclined to generate more car trips and fewer public transit trips. The coefficients of income indicate that residents with high incomes are inclined to generate more car and active trips and fewer public transit trips. This finding is consistent with most prior research [35]. The number of driver licenses facilitates generating more car trips. Car ownership is a significant contributor to the modality style. It not only is significantly associated with generating more car trips but also leads to using active modes and public transit less frequently. Residents from bigger households have more and less willingness to travel by car and public transit, respectively. This might be attributed to the fact that bigger households usually have more medical and educational needs, which have higher requirements for the comfort and convenience of travel [27,42]. Residents from households with children and elderly tend to travel by car more frequently. Meanwhile, residents from households with children tend to travel by public transit less frequently.

Regarding home BE features, all variables are significant contributors to the modality style. The coefficients of entropy indicate that diverse development strategies facilitate using active modes and public transit more frequently, but decrease the usage of cars. This result is consistent with most prior studies [43,44]. Residents living in neighborhoods with high bus stop densities have a higher tendency toward using public transit and traveling by car less frequently. The impacts of road density are significantly positive for the usage of active modes and public transit, whereas its impact on car trips is negative. Residents living far from the city center have a higher tendency toward using cars more frequently. Meanwhile, these residents are expected to travel by public transit less frequently. This finding might be because these areas usually have poor transit accessibility [45]. Population density is another factor influencing modality style. The results confirm high-density development strategies as a solution to restrict car use. This result is consistent with most existing prior studies [9].

As for workplace BE features, only the entropy, road density, and population density are found to be significant. Specifically, the coefficients of entropy indicate that diverse land use encourages active trips and declines car trips. Road density and population density are only positively associated with the usage of public transit, whereas their impacts on the generation of car and active trips are insignificant.

With regards to activity space BE features, although their impacts are smaller than the home BE features, they play a more essential role than workplace BE features. Specifically, we find that higher entropy is associated with using active modes more frequently. Meanwhile, the negative coefficient indicates its effectiveness in restricting car use. The coefficient of stop density is only statistically significant for the usage of public transit. The research of Fang et al. offers a potential reason for this finding, suggesting that residents usually have the intention to use public transport when the destination has better transit services [7]. Similar to the impact of stop density, higher road density is associated with using public transit more frequently. The coefficient of distance to city center is only significant for the usage of cars. Population density is also a factor influencing mobility habits. Residents who tend to participate in activities in high-density neighborhoods usually use active modes and public transit more frequently. Accordingly, higher density decreases car use.

5. Discussions and Conclusions

Motivated by the lack of evidence on the impacts of non-home BE features on the modality style and satiation effects from various travel modes, this study aimed to narrow the gaps by employing an MDCEV model to examine the impacts of BE features at multiple

locations on the modality style. It enriches the literature via (1) focusing on the impacts of BE features at home, work, and activity space locations; and (2) addressing the diminishing marginal rates of substitution among various modes, usage frequencies, and the overall satiation effects. The results advance the understanding of the role that BE features at different locations play in affecting the modality style. This study offers several research and planning implications.

Regarding methodology implementations, the MDCEV model advances the study of this topic via simultaneously exploring mode-specific determinants of whether and how the specific mode is used. On top of discussing the specific impacts of BE features, a picture of satiation effects is visualized from various travel modes, suggesting that despite a lower number of car trips being demanded with respect to the other modes, car traveling remains the most preferred travel mode.

This study provides some interesting insights into the built environment–travel behavior literature. The findings suggest BE features at home, work, and activity space locations as essential contributors to the modality style. Among the three locations, home BE features play the most important role in affecting, whereas the contributions of work BE features are fewer than two other locations. Among home BE features, only stop density and distance to city center are not significant contributors to the usage of active modes while the impacts of all other features are significant. Regarding workplace BE features, higher entropy promotes the usage of active modes and discourages the usage of cars. Higher road density and population density are significant contributors to the usage of public transit. As for activity space BE features, entropy is a significant contributor to the usage of active modes and cars while road density and stop density are the only significant contributors to the usage of public transit. Distance to city center only has a significant impact on the usage of cars, whereas population density is significant in affecting the usage of all three modes.

Regarding policy implications, the results highlight the importance of BE planning toward a sustainable city. Aiming to shift residents from car to active modes and public transit, a one-size-fits-all design is not an effective approach owing to the variant relationships between BE and travel across home, work, and activity space locations. It is of great importance for urban planners and policy practitioners to better understand the variant relationships and act according to local conditions. Moreover, planners and researchers may focus more on BE planning around residents' main activity spaces, such as gardens and catering and entertainment venues because a great deal of evidence has been provided on residential and workplace BE.

Some limitations remain in this study. First, the findings of this study were obtained based on a Beijing dataset. More data from other cities to confirm these findings and provide more robust results should be an essential direction of future studies. Second, the associations between BE at multiple locations and mode choice were analyzed based on cross-sectional data. Future studies should explore the causal mechanisms through a longitudinal or quasi-longitudinal design, which will help to seek more effective BE planning strategies. Third, the survey was conducted before the COVID-19 pandemic. There may exist differences between pre- and post-COVID scenarios. Future studies can compare the differences in the two scenarios and provide more refined policy implications.

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References

1. Brüchert, T.; Quentin, P.; Bolte, G. The relationship between perceived built environment and cycling or e-biking for transport among older adults–a cross-sectional study. *PLoS ONE* **2022**, *17*, e0267314. [CrossRef] [PubMed]
2. Ding, C.; Liu, T.; Cao, X.; Tian, L. Illustrating nonlinear effects of built environment attributes on housing renters' transit commuting. *Transp. Res. Part D Transp. Environ.* **2022**, *112*, 103503. [CrossRef]
3. Gan, Z.; Yang, M.; Feng, T.; Timmermans, H.J. Examining the relationship between built environment and metro ridership at station-to-station level. *Transp. Res. Part D Transp. Environ.* **2020**, *82*, 102332. [CrossRef]
4. Yang, M.; Wu, J.; Rasouli, S.; Cirillo, C.; Li, D. Exploring the impact of residential relocation on modal shift in commute trips: Evidence from a quasi-longitudinal analysis. *Transp. Policy* **2017**, *59*, 142–152. [CrossRef]
5. Wang, X.; Yin, C.; Zheng, C.; Shen, Y.; Shao, C. Integrating built environment and parking policy for car commuting reduction: Evidence from Beijing. *Transp. Plan. Technol.* **2023**, *46*, 888–911. [CrossRef]
6. Ding, C.; Zhou, X.; Cao, X.J.; Yang, J. Spatial and mediation analysis of the influences of residential and workplace built environments on commuting by car. *Transp. Res. Part A Policy Pract.* **2023**, *171*, 103662. [CrossRef]
7. Fang, J.; Yan, X.; Bejleri, I.; Chen, C. Which trip destination matters? Estimating the influence of the built environment on mode choice for home-based complex tours. *J. Transp. Geogr.* **2022**, *105*, 103474. [CrossRef]
8. Howell, N.A.; Farber, S.; Widener, M.J.; Allen, J.; Booth, G.L. Association between residential self-selection and non-residential built environment exposures. *Health Place* **2018**, *54*, 149–154. [CrossRef]
9. Wang, X.; Shao, C.; Yin, C.; Guan, L. Exploring the relationships of the residential and workplace built environment with commuting mode choice: A hierarchical cross-classified structural equation model. *Transp. Lett.* **2022**, *14*, 274–281. [CrossRef]
10. Vij, A.; Carrel, A.; Walker, J.L. Incorporating the influence of latent modal preferences on travel mode choice behavior. *Transp. Res. Part A Policy Pract.* **2013**, *54*, 164–178. [CrossRef]
11. Bhat, C.R.; Sardesai, R. The impact of stop-making and travel time reliability on commute mode choice. *Transp. Res. Part B Methodol.* **2006**, *40*, 709–730. [CrossRef]
12. Cervero, R.; Radisch, C. Travel choices in pedestrian versus automobile oriented neighborhoods. *Transp. Policy* **1996**, *3*, 127–141. [CrossRef]
13. Shamshiripour, A.; Rahimi, E.; Shabanpour, R.; Mohammadian, A.K. Dynamics of travelers' modality style in the presence of mobility-on-demand services. *Transp. Res. Part C Emerg. Technol.* **2020**, *117*, 102668. [CrossRef]
14. Cao, X.J.; Mokhtarian, P.L.; Handy, S.L. The relationship between the built environment and nonwork travel: A case study of Northern California. *Transp. Res. Part A Policy Pract.* **2009**, *43*, 548–559. [CrossRef]
15. Cheng, L.; De Vos, J.; Zhao, P.; Yang, M.; Witlox, F. Examining non-linear built environment effects on elderly's walking: A random forest approach. *Transp. Res. Part D Transp. Environ.* **2020**, *88*, 102552. [CrossRef]
16. Næss, P. Meta-analyses of built environment effects on travel: No new platinum standard. *J. Plan. Educ. Res.* **2022**, *42*, 199–205. [CrossRef]
17. Wu, J.; Tang, G.; Shen, H.; Rasouli, S. Spatial heterogeneity in the nonlinear impact of built environment on commuting time of active users: A gradient boosting regression tree approach. *J. Adv. Transp.* **2023**, *2023*, 6217672. [CrossRef]
18. Ewing, R.; Cervero, R. Travel and the built environment: A meta-analysis. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]
19. Wang, X.; Wang, W.; Yin, C. Exploring the Relationships between Multilevel Built Environments and Commute Durations in Dual-Earner Households: Does Gender Matter? *Int. J. Environ. Res. Public Health* **2023**, *20*, 4851. [CrossRef]
20. Sun, B.; Ermagun, A.; Dan, B. Built environmental impacts on commuting mode choice and distance: Evidence from Shanghai. *Transp. Res. Part D Transp. Environ.* **2017**, *52*, 441–453. [CrossRef]
21. Diao Mi Ferreira, J., Jr. Vehicle miles traveled and the built environment: Evidence from vehicle safety inspection data. *Environ. Plan. A* **2014**, *46*, 2991–3009. [CrossRef]
22. Ding, C.; Cao, X. How does the built environment at residential and work locations affect car ownership? An application of cross-classified multilevel model. *J. Transp. Geogr.* **2019**, *75*, 37–45. [CrossRef]
23. Wang, X.; Yin, C.; Zhang, J.; Shao, C.; Wang, S. Nonlinear effects of residential and workplace built environment on car dependence. *J. Transp. Geogr.* **2021**, *96*, 103207. [CrossRef]

24. Ding, C.; Wang, D.; Liu, C.; Zhang, Y.; Yang, J. Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. *Transp. Res. Part A Policy Pract.* **2017**, *100*, 65–80. [CrossRef]
25. Rahman, M.; Sciara, G.-C. Travel attitudes, the built environment and travel behavior relationships: Causal insights from social psychology theories. *Transp. Policy* **2022**, *123*, 44–54. [CrossRef]
26. Tao, T.; Næss, P. Exploring nonlinear built environment effects on driving with a mixed-methods approach. *Transp. Res. Part D Transp. Environ.* **2022**, *111*, 103443. [CrossRef]
27. Wang, X.; Shao, C.; Yin, C.; Guan, L. Built environment, life events and commuting mode shift: Focus on gender differences. *Transp. Res. Part D Transp. Environ.* **2020**, *88*, 102598. [CrossRef]
28. Zhang, W.; Zhang, M. Incorporating land use and pricing policies for reducing car dependence: Analytical framework and empirical evidence. *Urban Stud.* **2018**, *55*, 3012–3033. [CrossRef]
29. Zhang, M. The role of land use in travel mode choice: Evidence from Boston and Hong Kong. *J. Am. Plan. Assoc.* **2004**, *70*, 344–360. [CrossRef]
30. Yang, L.; Hu, L.; Wang, Z. The built environment and trip chaining behaviour revisited: The joint effects of the modifiable areal unit problem and tour purpose. *Urban Stud.* **2019**, *56*, 795–817. [CrossRef]
31. Ramezani, S.; Hasanzadeh, K.; Rinne, T.; Kajosaari, A.; Kyttä, M. Residential relocation and travel behavior change: Investigating the effects of changes in the built environment, activity space dispersion, car and bike ownership, and travel attitudes. *Transp. Res. Part A Policy Pract.* **2021**, *147*, 28–48. [CrossRef]
32. Limtanakool, N.; Dijst, M.; Schwanen, T. The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium-and longer-distance trips. *J. Transp. Geogr.* **2006**, *14*, 327–341. [CrossRef]
33. Guo, J.Y.; Bhat, C.R.; Copperman, R.B. Effect of the built environment on motorized and nonmotorized trip making: Substitutive, complementary, or synergistic? *Transp. Res. Rec.* **2007**, *2010*, 1–11. [CrossRef]
34. Larrañaga, A.M.; Rizzi, L.I.; Arellana, J.; Strambi, O.; Cybis, H.B.B. The influence of built environment and travel attitudes on walking: A case study of Porto Alegre, Brazil. *Int. J. Sustain. Transp.* **2016**, *10*, 332–342. [CrossRef]
35. Park, K.; Ewing, R.; Scheer, B.C.; Tian, G. The impacts of built environment characteristics of rail station areas on household travel behavior. *Cities* **2018**, *74*, 277–283. [CrossRef]
36. Yin, C.; Wang, X.; Shao, C. Do the Effects of ICT Use on Trip Generation Vary across Travel Modes? Evidence from Beijing. *J. Adv. Transp.* **2021**, *2021*, 6699674. [CrossRef]
37. Maat, K.; Wee, B.V.; Stead, D. Land use and travel behaviour: Expected effects from the perspective of utility theory and activity-based theories. *Environ. Plan. B Plan. Des.* **2005**, *32*, 33–46. [CrossRef]
38. Gao, J.; Yamamoto, T.; Helbich, M. The role of residential consonance and dissonance between couples in travel behavior. *Transp. Res. Part D Transp. Environ.* **2022**, *104*, 103196. [CrossRef]
39. Kim, S.-N.; Choo, S.; Mokhtarian, P.L. Home-based telecommuting and intra-household interactions in work and non-work travel: A seemingly unrelated censored regression approach. *Transp. Res. Part A Policy Pract.* **2015**, *80*, 197–214. [CrossRef]
40. Yin, C.; Shao, C.; Wang, X. Exploring the impact of built environment on car use: Does living near urban rail transit matter? *Transp. Lett.* **2020**, *12*, 391–398. [CrossRef]
41. Bhat, C.R. The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transp. Res. Part B Methodol.* **2008**, *42*, 274–303. [CrossRef]
42. Oakil, A.T.M.; Ettema, D.; Arentze, T.; Timmermans, H. Bicycle Commuting in the Netherlands: An analysis of modal shift and its dependence on life cycle and mobility events. *Int. J. Sustain. Transp.* **2016**, *10*, 376–384. [CrossRef]
43. Crane, R.; Crepeau, R. Does neighborhood design influence travel?: A behavioral analysis of travel diary and GIS data. *Transp. Res. Part D Transp. Environ.* **1998**, *3*, 225–238. [CrossRef]
44. Gehrke, S.R.; Clifton, K.J. An activity-related land use mix construct and its connection to pedestrian travel. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 9–26. [CrossRef]
45. Wang, X.; Shao, C.; Yin, C.; Dong, C. Exploring the effects of the built environment on commuting mode choice in neighborhoods near public transit stations: Evidence from China. *Transp. Plan. Technol.* **2021**, *44*, 111–127. [CrossRef]

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