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Impact of Residential Self-Selection on Low-Carbon Behavior: Evidence from Zhengzhou, China

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Abstract: Current resident lifestyles pose a significant threat to urban sustainable development. Therefore, low-carbon behavior is receiving increasing attention from scholars and policy makers. Ascertaining residential self-selection is essential in order to study the relationship between the built environment and travel behavior. While several studies have explored the relationship between the urban form, socioeconomic factors, and travel behavior, only a few of them have studied the impact of self-selection on household energy consumption and other forms of consumption, which are also contribute to household carbon emissions. Using large-scale field surveys of 1,485 households and high-resolution images, sourced from Google Maps in 2018, of Zhengzhou city, the present study estimated the low-carbon level of three kinds of behavior: daily energy use at home, daily travel, and daily consumption. The study investigated the influence factors on low-carbon behavior using the hierarchical linear model. We found that residential self-selection impacts both energy use and daily travel. Residents in some built environments consumed less energy at home and contributed less CO_2 emissions through daily travel than others. In particular, individual-level variables significantly affected the low-carbon energy use behavior. The female, elderly, highly educated, married, and working-class residents with children had higher levels of low-carbon energy use. Community-level variables significantly affected the level of low-carbon travel and low-carbon consumption. If residents lived in areas with high density, mixed land use, and high accessibility, their travel mode and consumption behavior would entail low carbon emissions. There is a relationship between individual variables and community variables. Different individual attributes living in the same built environment have different impacts on low-carbon behaviors.

Keywords: residential self-selection; low-carbon behavior; built environment; HLM; Zhengzhou

1. Introduction

With the acceleration of urbanization and industrialization, carbon emissions attributed to the residential self-selection have become for a significant contributory factor in greenhouse emissions. Numerous studies have found that residents living in the same built environment will have similar daily life behaviors [1–3]. What is less well understood is whether the observed patterns of behavior are attributed to the residential built environment itself or to attitude-induced residential self-selection, as a 'self-selected' result of individuals' changes in socioeconomic factors, lifecycles, and attitudes towards life behaviors [4]. Residential self-selection means that people choose residential areas of the specific built environment under the influence of factors such as their socioeconomic factors or their attitude preference levels to select similar behaviors of daily life [1–3]. If we do not consider residential self-selection, then we will overestimate the impact of the built environment on residents' daily life behaviors. Therefore, low-carbon lifestyles and/or behavior influenced by residential self-selection have been paid significant attention [5–8].

Residents' low-carbon behavior is a resource-saving and environmentally-friendly behavior. Its distinctive feature is reduced carbon emissions, which are attributed to less energy use at home, less or low-carbon daily travel, and less daily consumption [9–11]. As a subset of pro-environmental behavior [11], low-carbon behavior has dominated psychological fields for a long time [12]. Based on the theories of planned behavior (TPB) and value-belief-norms (VBNs), many scholars have analyzed the impact of an individual's environmental awareness, knowledge, attitude, and other factors on their carbon behavior [9,13,14]. For example, Li believes that an individual's attitude toward green consumption will affect their daily consumption behavior and the behavior of fellow residents [9]. Borgstede and Gadenne suggest that residents that are environmentally conscious are more likely to embrace low-carbon behaviors [15,16]. But the external environment also has a huge impact on the lives of residents. So, some studies have begun to pay attention to the significant impacts of individuals' attitudes and external environment on their behavior based on the attitudinal-behavior-circumstance (ABC) theory. These studies regard socioeconomic attributes and policy criteria as the external environment and analyzed the impacts of residents' gender, age, education, occupation, monthly income, housing type, environmental policies, and social criteria on low-carbon behaviors [8,14,17–21]. Ye and Yang suggest that women have higher levels of low-carbon behavior than men in terms of daily energy use at home [17,19]. Ye also believes that the elderly lifestyle is more focused on energy conservation [17]. Nicholls and Ding suggest that residents with high-education have higher levels of low-carbon behavior [14,22]. Ding suggest that civil servants and unit staff have higher levels of low-carbon behavior [8]. Allen and Thogersen suggest that environmental policies and social norms have a positive impact on residents' low-carbon behavior [20,21]. However, these studies do not involve the external living environment characteristics or the built environment, which is also closely related to peoples' lives. In fact, it is more operational and implementable to consider the built environment from the perspective of urban governance.

The built environment has a direct impact on residents' low-carbon behaviors [23]. The interaction between residents' daily behaviors and the built environment is significant for the transformation of low-carbon behavior [24]. The built environment factors usually include density, diversity, design, distance to transit, and destination accessibility [25]. The residents who dwell in areas with high density, highly mixed land use, and more road intersections tend to travel shorter distances and choose green travel modes [24,26–28]. For example, Cerin and Chaudhury suggest that people living in a compact residential area with highly mixed land use are more likely to choose public transport [29,30]. Zhang et al. suggest that people residing in areas with a high population density and well-connected street networks shorten their travel distances, and more residents choose non-motorized ways to travel, such as bicycles [24]. Ewing and Kroesen suggest that residents living in densely populated, highly mixed land use, pedestrian friendly and/or public transport residential areas are more likely to select green travel modes [26,31].

The relationship between the built environment and low-carbon behavior has been contentious. Some studies suggest that residents choose to live in areas conductive to green travel and consumption owing to attitude-induced residential self-selection as opposed to the built environment itself [2,32,33]. Existing studies verify the existence of residential self-selection from various perspectives [32,34]. Schwanen and Mokhtarian suggested that residents living in the coastal area of San Francisco that are concerned about the environment were more likely to live in high-density communities to reduce private car travel, while residents who liked private car travel would choose to live in low-density communities [35]. Cao et al. perceived that the farther the residential location was from the city center, the smaller the impact of self-selection on the travel distance was. The impact of the community built environment on VMT(VMT: vehicle-miles of travel) was 76% [36,37]. Zang et al. found that, after controlling the residential self-selection, the impact of the built environment decreases by 30%–50% when they analyzed the travel characteristics of older people in Hong Kong [24]. However, based on the study of samples from northern California, Cao et al. suggested that the impact of residential self-selection was minimal, and the built environment was still an essential factor influencing residents' travel behaviors [38]. Using the cross-lag panel model analysis, Wang et al. found that there was no residential self-selection in Beijing, while the direct impact of the attitude preference on travel behavior was stronger than that of the built environment [39].

To explore the effective relationship between the built environment and residents' behaviors, scholars used the omitted variables method and/or reverse causality method to study residential self-selection [1,3]. In particular, the omitted variables method supplemented relevant questions about behavioral preferences in the questionnaire [40,41]. Reverse causality was mainly investigated by the statistical control [42], sample selection model [42], structure equation mode (SEM) [2,3,43], nested model [44,45], and panel model [39,46–48]. Among them, the longitudinal design is a good method to study the causal relationship between the built environment and residents' behavior, because it can meet the time sequence of the causal relationship and control for travel attitudes. Therefore, Mokhtarian and Cao suggested that the longitudinal structural equation model may be the best method to reveal the complex relationship between the built environment, residential self-selection, and travel behavior [39,42]. However, most studies on residential self-selection were based on cross-section data [49]. Therefore, most scholars verified residential self-selection based on the reverse causal judgment [2,3,43–45,50].

Based on the literature review, the relevant studies suffer from the following problems. First, the built environment and socioeconomic factors are not distinguished. The built environment is the community level variable, whereas socioeconomic factors are the individual level variable. However, most studies rarely analyzed these influencing factors of residents' behavior from the perspective of two-level variables. Second, while the travel behavior has obtained significant attention, the energy use at home and daily consumption were ignored. In fact, carbon emissions from these three kinds exhibit a rebound effect, and one aspect of emission reduction may lead to an increase in carbon emissions from the other [51,52]. Third, the method of judging the choice of residence has not been unified, and we still need to determine it based on the research content and model method.

Therefore, we conducted a large-scale field survey in urban built areas in Zhengzhou and estimated the low-carbon level of three kinds of behavior—energy use at home, daily travel, and consumption, which could effectively avoid the rebound effect. The innovation of this research is to improve the method of verifying residents' self-selection, which has high applicability and rationality. In the study, we regarded the built environment as a community-level variable, and combined the correlation analysis with the null model in the HLM to judge the residential self-selection, which provides a new method to verify the existence of residential self-selection.

Our main research questions are as follows: (1) Is there residential self-selection in Zhengzhou? (2) How do socioeconomic factors at the individual level and the built environment at the community level influence low-carbon behaviors? (3) Does the built environment enhance or weaken the influence of individual level variables through residential self-selection? The following sections of this paper are as follows: The second part introduces data sources, research design, and variable selection. The third part includes the research methods and model selection of this paper. The fourth part is the analysis of the research results. The fifth part is a comparative discussion with other studies. The sixth part contains the research conclusions and related policy recommendations.

2. Materials and Methods

2.1. Data Source

Field survey data were the primary source of the individual level variable. We randomly selected 1,700 residents within the Fourth Ring Road of Zhengzhou city to carry out a questionnaire-based survey in May 2018. The percentages of the questionnaires were 9.2%, 31.8%, 40.1%, and 17.9%, respectively, from the first to the fourth ring road based on population distribution. In addition, to reflect housing differences, we chose houses constructed from 1980 to 2018 [2]. We adopted the method of on-site investigation in the household or community. The questionnaire covered the primary socioeconomic attributes of an individual (gender, age, marital status, education, occupation, monthly income), daily expenses, travel behavior characteristics, low-carbon cognition, and preferences. After eliminating the responses with vague positioning and incomplete information, we were left with 1485 valid questionnaires for analysis. The effective rate of the questionnaire was 87.4%. Then we estimated the low-carbon levels of residents' behaviors according to the Likert scale (the calculation method is given in Section 3.1).

Baidu POI and remote sensing image data (level 20, the spatial resolution of 0.27 m) were the primary data sources for the built environment. In this study, we described the built environment as "5D," that is, density, diversity, design, distance to transit, and destination accessibility [3,53,54]. Among them, density includes the plot ratio, population density, and building density. Diversity includes POI density and land use mixing degree. Design includes road network density and intersection density. Distance to transit is the shortest distance from the bus stop. Destination accessibility is the average accessibility to schools, shopping malls, parks, and hospitals. According to the research content, it is necessary to calculate the built environment of different communities. First, we calculated the built environment of 2494 communities in Zhengzhou based on POI data. Then, we divided each dimension index into high and low categories for permutation and combination (32 categories in total). Finally, we calculated the average value of each built environment index of 32 community layers and considered it as the built environment of the community level.

2.2. Research Design

This study focused on the interaction between built environment and socioeconomic factors from the perspective of residential self-selection. Therefore, the presence of residential self-selection is the basis of the research. Based on the concept of residential self-selection, we verified the existence of residential self-selection from two dimensions of cause and effect. We took the following two steps: First, we used correlation analysis to test whether there is correlation among residents' socioeconomic attributes, attitude preferences, and built environment. Then, we used the null model in the HLM to determine whether there is a difference in low-carbon behaviors among residents of different communities. When these two conditions are satisfied, we conclude that residents exercise residential self-selection.

The extent to which the built environment indirectly affects various low-carbon behaviors of residents may change owing to their varying socioeconomic factors. In this study, we used HLM to analyze the factors that influence low-carbon behavior, from both the individual- and community-level, to discuss the role of the built environment in enhancing or weakening the influence of individual-level variables. Based on the characteristics of HLM and the research content of this paper, we constructed a null model and calculated the inter-group correlation coefficient (ICC) index based on the variance results of the null model to analyze the differences of various low-carbon behaviors between groups. Next, we established a random-effects model to analyze the impacts of socioeconomic factors at the individual-level and the built environment at the community-level on various low-carbon behaviors. Finally, we built a complete model to analyze the interaction between community built environments and individual socioeconomic factors.

Because this study focuses on analyzing the influence mechanism of double-level variables on various low-carbon behaviors, we selected 18 variables from the individual- and community-level data sources and research contents (see Table 1).

Table 1. Variable selection and scale design.

Level	Category	Variables	Definition	Variable type
Individual level	Socioeconomic attribute	Gender (Gen)	1: Male; 2: Female	Classification
		Age (Age)	Actual age of respondents	Continuous
		Marriage (Mar)	1: Unmarried; 2:Married without children; 3: Married with children	Classification
		Education (Edu)	1: High school or less; 2:Bachelor or associate degree; 3:Bachelor degree or above	Classification
		Occupation (Occ)	1: Administrative staff 2: Corporate employee; 3: Freelancer; 4: Unemployed	Classification
		Monthly income (Mo-I)	1: <6000; 2: 6000-12000; 3:12000-20000; 4>20000	Continuous
	Attitude preference	Behavioral intention (Be-I)	Residents' acceptance of low-carbon behavior and the willingness to produce low-carbon behavior	Continuous
		Cognitive level (Co-L)	Residents' familiarity with low-carbon lifestyles	Continuous
		Cognitive environment (Co-E)	Opportunities and degrees of low-carbon knowledge that residents can perceive	Continuous
Community level	Built Environment	Plot ratio (Pl-R)	Ratio of total floor area to the base area	Continuous
		Population density (Po-D)	Number of people in a unit building area	Continuous
		Building density (Bu-D)	Proportion of building area in the built-up area	Continuous
		POI density (POI)	Degree of diversity of POI in the residential area	Continuous
		Land use mixing Degree (L-U-M)	Degree of diversification of various types of land use around residential areas	Continuous
		Road network density (R-N-D)	Ratio of the total length of the road network to the total is of the building	Continuous
		Intersection density (In-D)	Ratio of the number of intersections around the residential area to the building area	Continuous
		Distance to the bus stop (D-B-S)	Shortest distance from the nearest bus stop to the residential area	Continuous
		Accessibility (Acc)	Convenience of residents to the surrounding service facilities	Continuous

Figure 1 shows a two-level analytical framework of the low-carbon behavior in Zhengzhou residents. As can be seen from Figure 1, we concluded that there was an existence of residence self-selection if there is a correlation and there are inter-community differences among the low-carbon behaviors. The direct impact is to incorporate socioeconomic attributes, attitude preferences, and built environments into HLM to analyze the influencing factors of various low-carbon behaviors. The indirect impact is the result of the interaction impact of the two-level variables to explore how the built environment enhances or weakens the influence of individual-level variables through residential self-selection.

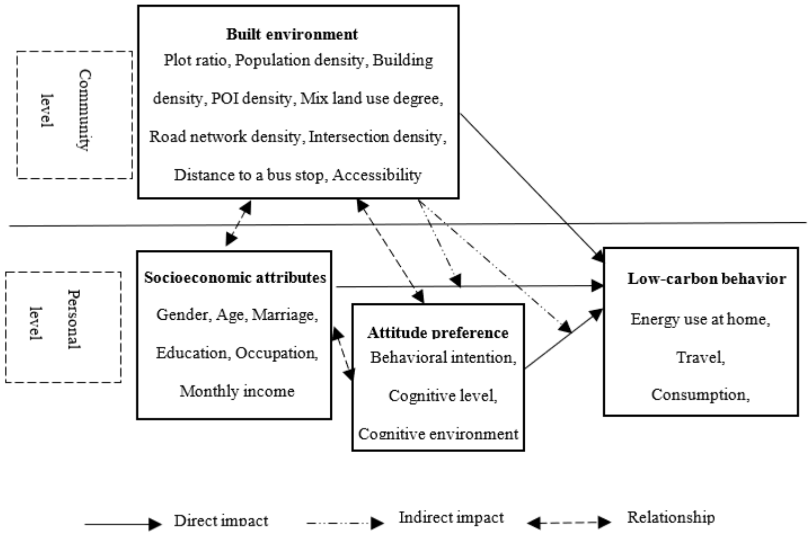

Figure 1. Multi-level analysis framework of the low-carbon behavior of residents in Zhengzhou city.

3. Research Methods

3.1. Quantification of Low-Carbon Behavior

This paper used the Likert scale and the Delphi method to measure the level of various low-carbon behaviors. The Likert scale method often takes the form of a 5-level scale and assigns an answer to the expressed attitude of each question with 1-5(e.g.,"very unfamiliar", "unfamiliar", "general", "familiar", "very familiar") [55]. The Delphi method, also known as the experts grading method, is a reasonable estimate of the qualitative problem by combining the experience and subjective judgment of several experts. Our questionnaires involve a lot of qualitative questions, and we can use the Likert scale and the Delphi method to rationally quantify the level of low-carbon behaviors. So, we first calculated the level of low-carbon behavior based on the Likert scale and Delphi method, and then averaged them to ensure that the scores of low-carbon behavior were at (0,5). Because household carbon emissions are divided into direct, travel, and implied carbon emissions, we measured the low-carbon behavior of residents from three dimensions of daily energy use at home, travel, and consumption. The calculation basis of various low-carbon behaviors is as follows.

The usages of various household appliances and general cost of living in the questionnaire are used to calculate the level of energy use and consumption behavior. First, we calculated the average durations of use of various household appliances and the average cost of living (X). Then, based on the values of 1, 1.5, 2, and 3 times of X, we assigned the questionnaire scores to 5, 4, 3, 2, and 1. Finally, we averaged the low-carbon behavior by the number of categories, and the level of low-carbon energy use and consumption behavior of residents were estimated. The travel frequency (Tr-F), travel distance (Tr-D), and travel mode (Tr-M) for various activities in the questionnaire were used to calculate the level of low-carbon travel. We assigned weights based on the travel frequencies for various activities in the questionnaire and assigned values to travel distances and modes of transport. After multiplying the values, the score of low-carbon behavior was calculated (Table 2). The calculation formula for the low-carbon travel level is as follows:

$$Sc = \frac{1}{n}\sum_{j=1}^{m}(K_j A_j B_j) \quad (1)$$

where m is the number of questionnaires concerning the low-carbon behavior, n is the number of residential activity categories, K_j is the travel frequency weight of class j activities, A_j is the travel distance of class j activities, and B_j is the travel mode assignment of class j activities.

Table 2. Low-carbon travel level assignment table.

Tr-F	W-G (K)	Tr-D	Tr-M	Ca-E (g/km)	As (A or B)
Once a month, once a year, twice a year, three times a year or more	1	$[0,\overline{X})$	Walking, bicycle	0	5
Three times a month or more, twice a month	4/5	$[\overline{X},1.5\overline{X})$	Electric car, motorcycle	8	4
Twice a week, once a week	3/5	$[1.5\overline{X},2\overline{X})$	Subway, other	9.1	3
Once a day, three times a week and above	2/5	$[2\overline{X},3\overline{X})$	Bus, unit shuttle, shopping bus	35	2
Three times a day or more, twice a day	1/5	$[3\overline{X},+\infty)$	Car, taxi	135	1

Note: W-G, Ca-E, and As are weight, carbon emissions, and assignment, respectively.

3.2. Hierarchical Linear Model

Hierarchical Linear Models (HLMs) are widely used in sociology and psychology research. They construct different levels of regression models to analyze the effects of each level of variables on the dependent variables, and further explore the interaction between the various levels of variables, which can avoid the analysis error generated by analyzing the multi-level structure data from a single level [56]. Therefore, geographers have begun to accept the HLM model. Combined with the research subject of this paper, the level of low-carbon behavior of residents is influenced by individual factors and built environment. However, previous studies have not paid enough attention to the interaction between community built environments and an individual's socioeconomic factors. This study aimed to analyze the impact of variables on different levels and the interaction of two-level factors [27]. Therefore, we chose the HLM in our research involving three submodels: null model, random model, and complete model [57,58], while the relevant formulas were as follows:

(1) Null model: The null model comprises only the Y variable and is the basis of HLM. Based on the results of the null model, we obtained the intra-group and inter-group variances for various low-carbon behaviors and calculated their ICC indices. ICC is the proportion of the variance between groups to the total variance. The closer the value is to 1, the greater the difference between groups of low-carbon behaviors, that is, the more similar the daily life behavior of residents living in similar communities. Cohen suggested that when ICC is greater than 0.059, it is necessary to carry out HLM [56,59]. Specific formulas are as follows:

$$\text{Individual level}: \ \mathrm{Y_{ij}} = \mathrm{B_{0j}} + \mathrm{R_{ij}} \quad (2)$$

$$\text{Community level}: \ \mathrm{B_{0j}} = \mathrm{G_{00}} + \mathrm{U_{0j}}. \quad (3)$$

(2) Random model: It is based only the individual- or community-level variables, which are used to analyze the impact of individual or community variables on various low-carbon behavior [56]. Specific models are as follows:

$$\text{Individual level}: \mathrm{Y_{ij}} = \mathrm{B_{0j}} + \mathrm{B_{1j}X_{ij}} + \mathrm{R_{ij}} \quad (4)$$

$$\text{Community level}: B_{0j} = G_{00} + U_{0j} \tag{5}$$

$$B_{1j} = G_{10} + U_{1j}. \tag{6}$$

(3) Complete model: This complete model includes two-level variables of the individual and community. The slope of an individual level is used as a dependent variable to reflect the interaction between variables of each level [60]. The calculation formula is as follows:

$$\text{Individual level}: Y_{ij} = B_{0j} + B_{1j}X_{ij} + R_{ij} \tag{7}$$

$$\text{Community level}: B_{0j} = G_{00} + G_{01}Z_j + U_{0j} \tag{8}$$

$$B_{1j} = G_{10} + G_{11}Z_j + U_{1j} \tag{9}$$

where Y_{ij} is the low-carbon behavior level of i residents in the j community, B_{0j} is the intercept, R_{ij} is the error term, B_{1j} is the coefficient of X_{ij}, X_{ij} is an individual-level variable (such as gender, age, occupation, and other such attributes), and Z_j is a community-level variable (such as plot ratio, population density, and other built environment attributes). Equations (7)–(9) represent the interactions between the built environment and the individual factors, that is, whether the indirect impact of the built environment on various low-carbon behaviors of residents will change owing to different individual characteristics [56,57].

4. Multi-level Impact Factors and the Impact Mechanism of Low-Carbon Behavior of Residents

4.1. Correlation Analysis

First, this study analyzed the correlation between individual factors and built environment to ascertain the residential self-selection of Zhengzhou residents. As shown in Figure 2, the socioeconomic attributes (gender, age, marital status, occupation, education, monthly income) of residents have a certain correlation with the built environment; the attitude preferences (behavioral intention, cognitive level, and cognitive environment) of residents have a positive or negative correlation with the built environment. Combining the study design presented in Section 2.2 and Figure 2, we find that there is a certain correlation among the socioeconomic factors, attitude preferences of residents, and the built environment of residential areas. This is the first condition that indicates that residents have exercised residential self-selection. Then, according to the results of the null model, the ICC index of all kinds of low-carbon behavior was calculated. If there are variations among communities, we can conclude that residents of the Zhengzhou city have exercised residential self-selection.

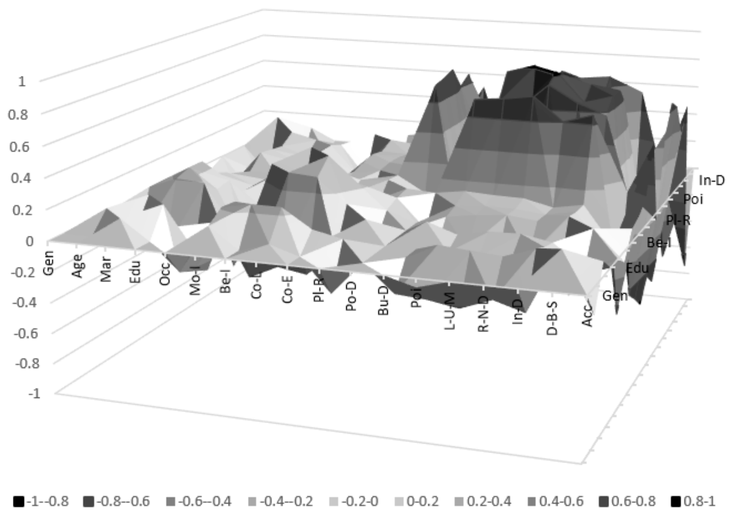

Figure 2. Correlation analysis of two-level variables in Zhengzhou city.

4.2. Multi-Level Influencing Factors of Low-Carbon Behavior of Residents

4.2.1. Null Model

First, we constructed a null model to obtain the intra-group and inter-group variances of various low-carbon behaviors and calculated ICC to determine whether there is inter-community variation in the low-carbon behavior of residents. As shown in Table 3, the ICC of low-carbon energy use, daily travel, and consumption behavior are 0.166, 0.552, and 0.781, respectively. This shows that there are differences among various communities. Because of the community-level differences in various low-carbon behaviors, we can conclude that the residents of Zhengzhou have exercised residential self-selection. Furthermore, Cohen suggested that when the ICC value is significantly higher than 0.059, HLM analysis is required [56,59].

Table 3. Variance estimates of various models of low-carbon behavioral factors.

	En-U-B	Tr-B	Co-B
In-G	2.073***	1.827***	0.476***
Be-G	0.412***	2.254***	1.699***
ICC	0.166	0.552	0.781

*: P < 0.1; **: P < 0.05; ***: P < 0.01. In-G is intra-group variance; Be-G is variance between groups. En-U-B, Tr-B, and Co-B are low-carbon energy use, travel, and consumption behavior, respectively.

4.2.2. Individual-Level Variables

Individual-level variables will have a positive correlation on residents' low-carbon behavior. Therefore, this paper incorporates individual-level variables into the model to analyze the impact of individual socioeconomic factors and attitude preferences on residents' low-carbon behavior. The results are shown in Table 4.

Table 4. Models of low-carbon behavior influencing factors, including individual- and community-level variables.

Category	Variable	En-U-B	Tr-B	Co-B	Category	Variable	En-U-B	Tr-B	Co-B
S-E-A	Gen	0.115**	−0.119*	−0.006	B-E	Pl-R	−0.045	0.084	−0.087
	Age	−0.001	0.002	0.009***		Po-D	−3.211	−1.021	−2.768
	Mar	0.432***	−0.117**	−0.124***		Bu-D	0.518	5.593	−1.387
	Edu	−0.031	0.052	0.085***		POI	0.002	0.006	0.003
	Occ	−0.244***	−0.029	−0.139***		L-U-M	−5.314	11.766*	−21.021**
	Mo-I	0.369***	0.038	0.170***		R-N-D	0.02	0.022	−0.086***
A-P	Be-I	0.327***	0.33***	0.007		In-D	−0.002	0.028	−0.031
	Co-L	0.232***	0.057	0.021		D-B-S	−0.002	−0.002*	0.002*
	Co-E	0.038	0.185***	0.014		Acc	−0.11	0.267***	0.469***
Va	In-G	0.966***	1.504***	0.418***	Va	Be-G	0.341***	0.247***	0.354***
Te	C-S	349.73***	134.42***	114.83***	Te	C-S	137.64**	62.28***	97.367***

*:P < 0.1;**:P < 0.05;***:P < 0.01. Each variable is abbreviated. For meanings of abbreviated variables, refer to Tables 1 and 3. Va is variance; Te is test; C-S is Chi-square; In-G is intra-group variance; Be-G is variance between groups.

(1) Socioeconomic factors. These factors significantly affect residents' levels of low-carbon energy use and consumption behavior. Similar to the results of Ding, Yang, and others [8,19], women more commonly present low-carbon behavior in daily energy use and appliance selection owing to differences in their consumption habits and role division. However, according to Table 4, women tend to choose high-carbon travel modes such as motorization. The study by Yang et al. shows that age has a significant positive impact on the low-carbon consumption behavior of residents [19]. Older people are affected by living habits and physical conditions, and consumption behavior may be simplistic.

However, owing to the diversification of consumption types and higher consumption levels, young people show a high carbon behavior in daily consumption.

Marital status also affects residents' daily life behavior. Because the married families with children have a large population base, high cost of living, high carbonization of travel behavior, and energy use at home, their daily consumption will tend towards energy conservation and environmental protection. Similar to the results of Ding and Yang et al. [14,19], the educational background has a positive impact on residents' level of low-carbon consumption behavior. Highly educated residents generally have higher cultural literacy and are more receptive to low-carbon knowledge, and their daily consumption tends toward low carbon behavior. As the results of Ding et al. show [14], the daily lives of administrative staff and enterprise staff show a low carbon behavior, while those of unemployed residents, such as students, reflect a high-carbon behavior. Because most employed residents need to bear the living expenses of the whole family and the economic burden is relatively significant, the energy use at home and daily consumption behaviors tend to not be highly carbon intensive. Similar to the results of Poruschi and Ramos [60,61], monthly income has a significant impact on residents' low-carbon behavior. Although high-income residents have diversified consumption, they can buy energy-efficient appliances and household items. Also, high-income residents are likely to be highly educated residents, with a stronger awareness of a low-carbon lifestyle and its benefits.

(2) Attitude preference. Similar to the results of Li and Ding Z et al., residents with positive attitudes and preferences show higher levels of low-carbon behavior [9,14]. The behavior intention of low carbon is the acceptance of low-carbon behavior by residents and the willingness to form low-carbon behavior. Table 4 shows that when residents' behavior intention increases by one unit, the low-carbon level of residents' energy use and travel behavior increases by 0.327 and 0.33 units. The cognitive level of low-carbon behavior is the residents' familiarity with the low-carbon lifestyle. Table 4 shows that residents' cognitive level has a positive impact on their low-carbon energy use level. For each unit of residents' cognitive level, the level of low-carbon energy use increases by 0.232 units. The cognitive environment of low carbon is the opportunity and extent which residents are exposed to low-carbon knowledge. The higher the contact of residents to low-carbon knowledge, the greater the invisible externalization of residents' daily life behavior. Table 4 shows that when the low-carbon cognitive environment increases by one unit, the low-carbon travel behavior level of residents increases by 0.185 units.

By comparing the intra-group variance of low-carbon behavior with the null model in Table 3 and the intra-group variance of low-carbon behavior in Table 4, the variance reduction rates of low-carbon behavior were 0.534, 0.1768, and 0.1218. The results show that the individual's socioeconomic factors and attitude preference variables explain 53.4%, 17.68%, and 12.18% of differences, respectively, in low-carbon energy use, travel, and consumption behavior. These indicate that low-carbon consumption behavior is significantly affected by individual socioeconomic and attitude preference factors.

4.2.3. Community Level

Although Model 2 believes that individual-level variables affect the level of low-carbon behavior, the community-level variables are also important reasons for the low-carbon behavior among residents. Therefore, we incorporate built environmental variables into the model to analyze their impact on various low-carbon behaviors of residents. The results are shown in Table 4.

The analysis results show that the built environment significantly affects residents' low-carbon travel and consumption behavior; however, the impact on some indicators is the opposite. The plot ratio, population density, and building density have no significant impact on all kinds of low-carbon behavior of residents, but there are still some positive and negative effects. The degree of land use mixing positively affects low-carbon travel behavior and negatively affects low-carbon consumption behavior. As shown in Table 4, if the land use mixing degree around the residential area increases by one unit, the residents' level of low-carbon travel increases by 11.766 units and consumption behavior decreases by 21.021 units. There is a high degree of land mixing around the residential area and rich land use, and the occupational–residential distances are not significant. Residents choose walking or non-motorized vehicles for daily travel. However, a high degree of mixing will increase the probability of residents contacting consumption, which may prompt residents to increase consumption.

Road network density will reduce the level of low-carbon consumption behavior of residents. The density of the road network can reflect accessibility and street design. Most high-density areas have well-established infrastructure and excellent accessibility, and the residents living in such areas are more likely to have a diversified consumption. Bus station distance negatively affects low-carbon travel behavior and positively affects low-carbon consumption behavior. As shown in Table 4, we found that for each additional unit of the shortest distance between bus stations and residential areas, the level of low-carbon travel decreases by 0.002 units and consumption behavior increases by 0.002 units. Owing to the influence of distance attenuation, with the increase in the shortest distance to bus stations, residents are more likely to choose a motorized travel; however, most of the areas far from bus stations have imperfect infrastructure, the service facilities are low, and the economic level of residents is mostly low. Therefore, under the impact of economic conditions and the external environment, consumer behavior has gradually shifted to low-carbon one. Accessibility has a positive impact on residents' low-carbon behavior. As shown in Table 4, for every unit increase in the accessibility of residential areas, the level of low-carbon travel and consumption behavior will increase by 0.267 and 0.469 units. With improvements in accessibility, residents will choose a low-carbon and efficient non-motorized way to perform daily activities.

Comparing the null model of Table 3 with the variance of various low-carbon behavior groups after adding the community-level variables in Table 4, the variance reduction rates of various low-carbon behaviors are 0.1723, 0.8904, and 0.7916. That is, the built environment explains 17.23%, 89.04%, and 79.16% of the low-carbon energy use, travel, and consumption behavior of residents, respectively. The community level of low-carbon travel and consumption behavior is the highest level, indicating that the built environment has a significant impact on residents' low-carbon travel and consumption behavior.

4.2.4. Complete Model

The above analysis shows that the level of low-carbon behavior is affected by the individual's socioeconomic factors, attitude preference factors, and built environment. Next, the interaction of the two-level factors is analyzed. Therefore, we incorporated all the variables into the complete model to analyze the interaction between the built environment, socioeconomic factors, and attitude preference variables. The results of the model are shown in Figure 3.

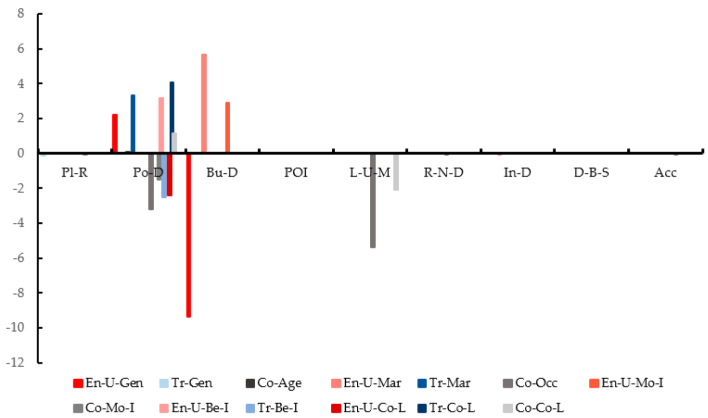

Figure 3. Interaction between individual and community layers of various low-carbon behaviors. Note: For expansions of abbreviated variables, refer to Tables 1 and 3; "-" represents the interaction between variables.

From the perspective of built environment factors, population density, land use mixing degree, and housing density have a significant indirect impact on various low-carbon behaviors, which will enhance or weaken the impact of an individual's socioeconomic factors on their low-carbon behavior. As shown in Figure 3, we find that for every unit of increase in population density, the impact of gender, marital status, and behavioral intentions on low-carbon behavior increased by 2.213, 3.324, and 3.18 units, respectively. However, the impact of the monthly income and cognitive level on low-carbon behavior is reduced by 3.177 and 2.417 units, respectively. With an increase in housing density per unit, the impact of marital status and monthly income on low-carbon behavior increased by 5.646 and 2.894 units, respectively; whereas the impact of gender on low-carbon behavior decreased by 9.336 units. With an increase in land use mixing degree by one unit, the impact of monthly income and cognitive level on residents' low-carbon behavior is reduced by 5.377 and 2.094 units, respectively.

Low-carbon behavior is indirectly affected by the built environment; that is, different individuals' socioeconomic factors living in the same built environment have different impacts on their low-carbon behavior. Combining the results of Table 4 and Figure 3, as far as daily energy use at home is concerned, if female residents live in high population density areas, their level of low-carbon energy use behavior is higher. Residents with children and high monthly incomes living in high-density housing areas will increase their level of low-carbon energy use. In terms of daily travel, female residents living in high housing density will weaken their level of low-carbon energy use behavior. Unmarried residents living in high population density areas with a high cognitive level will improve their level of low-carbon travel behavior; however, residents living in high population density areas with positive behavioral intention will weaken their level of low-carbon travel behavior. As far as daily consumption is concerned, old age residents living in high population density areas will increase their level of low-carbon consumption behavior; however, residents living in high population density areas with retired people and a high monthly income will weaken their level of low-carbon consumption behavior. Residents living in high-level land use with high-cognitive levels will have lower levels of low-carbon consumption behavior. Residents living in high accessibility areas with high levels of awareness have improved levels of low-carbon consumption; whereas, high-income people living in high accessibility areas have a reduced level of low-carbon consumption behavior.

4.3. Analysis of Influence Mechanism of Low-Carbon Behavior under Residential Self-Selection

Owing to the prevalence of residential self-selection, some scholars suggest that the correlation between the built environment and behavior may be the cause of personal socioeconomic and attitude preferences. Therefore, it is necessary to analyze the interaction among the built environment, individual's socioeconomic factors, and attitudinal preference variables and further explore whether the indirect impact of built environment on various low-carbon behaviors of residents will change due to different individual characteristics.

First, according to the correlation test and the results of null model, we find that there are correlations between the two-level factors of individual's socioeconomic factors, attitude preference, and built environment. Also, the ICC index shows that there are inter-community variations among low-carbon behaviors in Zhengzhou. Because of the influence of socioeconomic factors and attitude preferences, residents choose the built environment of residential areas and thus have a similar lifestyle to that of their neighbors [30,36,44]. Therefore, the above results illustrate the self-selection of Zhengzhou residents.

Second, in residents' daily life behavior, they may follow the criterion of "from inside to outside." Based on their characteristics and living environment, they may choose an appropriate lifestyle, and then adjust their behavior according to the interaction between the external living environment and individual attribute variables. Therefore, with the transaction of housing, residents with similar socioeconomic attributes tend to live in the same built environment, which leads to a certain degree of residential differentiation.

Finally, there is a complex interaction between the built environment and the individual characteristics. The indirect enhancement or weakening impact of built environment on various low-carbon behaviors is different under different individual characteristics. The impact of different socioeconomic characteristics on low-carbon behavior will change with the built environment. Therefore, in the related research in the future, we should pay attention to the spatial-behavioral interactions of various low-carbon behaviors, which are complex and may be nonlinear.

5. Discussions

This study proposes a new method for ascertaining residential self-selection from the two dimensions of cause and effect. The previous research methods are mostly based on missing variables or reverse causality, or both sources are considered to ascertain the residential self-selection [40]. However, because residential self-selection involves cause and effect, previous research methods may lack adaptability. For example, while Schwanen and Chatman added questions about attitude preferences in their questionnaires [40,41], they did not pay enough attention to residents' similar daily behaviors. Cao and Xu used propensity scores to match the relationship between the dwelling position and daily behavior; however, the attitude preference factor is measured by dichotomy, which may not capture significant changes in attitude preference [38]. Based on the results of the nested model, Cervero suggested that the living near a traffic stop will affect the choice of travel mode [44]. However, Cervero's study did not consider the impact of attitude preferences and did not incorporate the built environment into the community-level variables. We combined the correlation analysis with the null model in the HLM to ascertain residential self-selection in Zhengzhou residents. Consequently, we verified the residential self-selection from the following two points: there is a correlation between two-level variables, and the low-carbon behavior varies among groups. Based on the concept of residential self-selection, the present study started from the perspectives of cause and effect, and considered the built environment, nested effect, and attitude preference variables. This method has stronger applicability and operability in practical research.

This study provides a new perspective for studying various low-carbon behaviors. Most previous studies focused on one aspect of daily energy use at home, daily travel, and daily consumption. However, the residents' daily life behaviors may have a rebound effect, that is, one aspect of emission reduction will lead to an increase in carbon emissions in another aspect [51,52]. Among them, we found that some research results are inconsistent. First, Poruschi and Ramos suggest that high-income households are more active in low-carbon behavior [60,61], however, Yang suggests that low-income families are more likely to accept low-carbon consumption behaviors [19]. The cause of the inconsistency may be due to different research subjects. Poruschi and Ramos study the daily life behavior of residents, and Yang only considers daily consumption behavior. Ye and Yang believe that women's awareness of conservation is more positive in terms of household daily energy use at home [17,19], However, our research suggests that women can have a low-carbon awareness in daily energy use at home, but they tend to choose a motorized mode of travel. Finally, Ewing and Kroesen suggest that residents living in highly mixed land use are more likely to select green travel modes [26,31]. Our study validated this result, but also found that the level of low-carbon consumption behavior of residents in such a region decreases. All of these results illustrate the rationality of considering low-carbon behavior of residents from the three aspects of daily energy use at home, daily travel, and daily consumption. Therefore, this study considers the influencing factors of three types of low-carbon behaviors and formulate more targeted policy recommendations.

6. Conclusions and Policy Suggestion

6.1. Conclusions

The objective of this study was to ascertain the existence of residential self-selection from two dimensions of cause and effect, and then determine the variables of the individual-levels and community-levels, as well as the effects of two-level interaction on various low-carbon behaviors.

After analyzing a sample of 1485 households in Zhengzhou, we found that residents of Zhengzhou City have residential self-selection, and the residential self-selection has a greater impact on energy use behavior and daily travel behavior. Most scholars only refer to travel behaviors in the study of residential self-selection, but our found that residential self-selection impacts both energy use and daily travel. In particular, individual-level variables significantly affect low-carbon energy use behavior. The female, elderly, highly educated, married, and working-class residents with children had higher levels of low-carbon energy use. Community-level variables significantly affect the level of low-carbon travel and low-carbon consumption. The travel mode of residents living in areas with high density, mixed land use, and high accessibility would be low-carbon. There is an interaction between individual variables and community variables. Residents with different individual attributes living in the same built environment have different impacts on low-carbon behaviors. If residents with children and high monthly income live in high housing density areas, their level of low-carbon energy use behavior will be enhanced; however, for female residents living in high housing density areas, the level of low-carbon energy use will be weakened. Residents living in high population density areas with high levels of cognition and the elderly have improved their level of low-carbon consumption behaviors; whereas, those living in high population density areas with high monthly incomes have weakened their level of low-carbon consumption behaviors.

6.2. Policy Suggestion

This study suggests that there are variations in the driving forces and impacts of various low-carbon behaviors. Moreover, individual- and community-level variables influence residents' low-carbon behaviors. Considering the interaction between the two levels, it is found that residents with different socioeconomic attributes living in the same built environment have different impacts on indirect enhancement or weakening of various low-carbon behaviors. Therefore, we summarize the influencing factors of various low-carbon behaviors and accordingly propose corresponding policy recommendations to change the daily behavior of residents.

(1) Strengthen low-carbon knowledge by way of publicity and education. Policy initiatives by governments and their community implementation can help change the daily behaviors of residents. Apart from the individuals' socioeconomic factors and attitude preferences, their internal cultural literacy of low-carbon and cognitive level of low-carbon will affect their low-carbon behaviors. Therefore, we should increase residents' recognition and acceptance of low-carbon knowledge through the formulation of relevant low-carbon policies and community publicity policies.

(2) Create compact and self-supporting communities. The government should carefully locate the city centers and plan the layout to ensure the rationality and convenience of the surrounding infrastructure, and then strengthen the guiding role of the external living environment on the residents' lifestyle. Our study found that residents' daily travel behavior is closely related to the external environment, and increasing the land use mix degree and accessibility will improve residents' low-carbon behavior levels. However, if residents live in areas with a high land mix and dense road networks, their daily consumption will increase. Therefore, we need to guide residents' daily lifestyles through various measures, such as improving the mix of land use, shortening the distance between bus stops, and improving accessibility.

(3) Modify the lifestyle of residents in line with local conditions. The government should make policy recommendations based on the type of community. For example, residents in densely populated areas should be not only exposed to low-carbon publicity but should also be provided with appropriate

subsidies and incentives. However, for residents living in areas with a high land mix, it is necessary to highlight the advantages of low-carbon living behaviors and reduce these residents' low-carbon behavior-cognition gap. Therefore, there is a need to develop targeted countermeasures to make residents' daily activities more compliant with low-carbon behavior.

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