Investigate the relationship between green space and active travel of students: using Beijing as case studies

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Abstract. Active travel is getting popular in urban studies worldwide as it can decrease the carbon emission. This study builds on recent interest in green space and active travel to further investigate the links between green space and students' active travel behavior at the university campus. To better understand these relationships, this study assessed the green spaces of the universities using the remote sensing data and street-view images based on deep learning technology. By using these data combined with multilevel logistic regression modelling, the results of our study indicate a positive relationship between the eye-level green space and the active travel behavior of the university student on a semi-enclosed Chinese university campus. These results emphasize the importance of campus green space on the active travel behavior of university students and the implication of future transportation to achieve green and low-carbon society.

Keywords: Active travel; University students; Green space; Urban Planning.

1. Introduction

The transportation is a key industry for energy saving and emission reduction in China, and it is important to study carbon reduction measures in transportation (Le et al., 2021). Active travel (AT) advocates the formation of "low-pollution, low-energy" travel mode. With China's "double carbon" (carbon peaking and carbon neutrality) policy, China has taken active measures to promote active travel patterns, but has not yet achieved satisfactory results. Since residents' willingness to make active travel plays a crucial role in alleviating the problems caused by transportation, many studies have focused on this, but young people are still a significantly neglected group in studies on active travel (Hu et al., 2021). The university student groups not only occupies an important position in transport activities, but also during the years in universities is a stage when students develop travel behavior patterns. Therefore, promoting active travel among university students is one of the effective ways to reduce transport carbon emissions.

Urban green spaces are considered to be an effective means of promoting active travel (Grigoletto et al., 2022), however, existing studies have not always obtained a positive effect of green spaces on AT (Wu et al., 2020). Ramezani et al. (2019) have found that green spaces exposed to the built environment have a positive effect on individual's personal goals of performing physical activities and sports, which in turn influenced travel behavior. However, the study by Maki-Opas et al. (2016) found that a high percentage of green space had a negative impact on commuting. This inconsistent result could be caused by the different types of green exposure assessment used (Giannico et al., 2022). In addition, there are fewer studies related to built environment factors that influence active travel in specific study groups, especially university students (Sims et al.,2017). Previous studies has shown that some universities have been exploring their green areas by promoting activities that benefit the local and academic communities (Almashhour and Samara,2022), however, more actions could be taken to harness the ecological potential of the campus.

In this study, the study attempts to fill this gap by exploring the link between green space and active travel among university students. In particular, this study focused on the university campuses and consider two indicators of green space assessments (Normalized Difference Vegetation Index (NVDI) and Green Landscape Index (GVI) with two types of travel modes (walking and cycling). The university students were chosen for the study because university campuses are an important part of the urban green open space system and make an important contribution to the landscape of the cities in which they are located (Aciksoz et al., 2014). Green spaces on campuses, which are also considered to be an important element of urban greenery, provide many benefits to university students (Li et al., 2019). Six colleges and universities in total in Haidian District, Beijing, were selected as empirical study cases because it is a highly dense area with numerous enclosed university campuses (Sun et al., 2011). This study explored the association between urban greenery and students' AT behavior on gated university campuses in China using data from remote sensing data, street-view images and questionnaires, and analyzed them using multilevel logistic regression models. With the growing advocacy for low-carbon travel, six universities in the Haidian District of Beijing could be a useful case study for exploring the relationship between green space and active travel among university students on Chinese closed university campuses.

2. Methodology and Materials

2.1 Study area

The study area is selected from six university campuses in Haidian District, Beijing. The density of universities in Haidian District is high, and the difference of green space within different campuses is significant. Most of the university campuses in China are bounded by walls, and the campuses are relatively closed and less open, therefore using the university campuses as the research sites can clarify the boundaries of the site, and can also study the active travel behavior of university students.

2.2 Data source

Six university students in Haidian District, Beijing were selected as the sample through multi-stage randomized whole group sampling. Within the selected university campus area, the study population included students from six universities: Tsinghua University, Peking University, Beijing Foreign Studies University, Beijing Jiaotong University, Beijing Institute of Technology, and Beijing University of Posts and Telecommunications. The questionnaire designed for this study included variables such as active travel tendency, transport characteristics, and basic demographic data to determine the characteristics of the study group. The questionnaire was distributed through online and third-party platforms on September 5, 2022, and 1167 questionnaires were collected in six schools as of November 5, 2022. After manually screening samples that did not fit this study (eg. samples that were too old, schools that did not fit, and missed questions), a total of 968 valid questionnaires were collected, followed by field interviews with 32 respondents, resulting in a harvest of 1000 valid questionnaires were used as the study population sample for this study. Descriptive statistics of the study population are as follows (Table 1)

Table 1 Descriptive Analysis

	Variables	Categories	Proportion (numbers)/Mean (SD)
Dependent variables	Active travel tendency	Yes	62.8 (628)
		No	37.2 (372)
Independent variables	GVI (%)		30.04 (5.038)
	NDVI (%)		16.06 (2.615)
Demographic variables	Gender	Male	48.6 (486)
		Female	51.4 (514)
	Age (years)		22 (5.20)
	Educational attainment level	Specialist and below	40.4(404)
		Undergraduate	40.6(406)
		Postgraduate	16.7(167)

		Doctor and above	2.3(23)
	Income	<2,000 RMB per month	7.7(77)
		2,000-3,000 RMB per month	33.7(337)
		3,000-4,000 RMB per month	40.6(406)
		>4,000 RMB per month	18.0(180)
	Hukou status	Local hukou	40.1(401)
		Non-local hukou	59.9(599)
	Partner relationship status	Partner relationship	19.3(193)
		No partner relationship	80.7(807)
	Campus Area (hm2)		154.1 (155.1)
Transport characteristics	Driving licence	Yes	56.8(568)
		No	43.2(432)
	Car ownership	Yes	13.5(135)
		No	86.5(865)
	Bike ownership	Yes	41.5(415)
		No	58.5(585)
	E-bike ownership	Yes	66.2(662)
		No	33.8(338)
	Shared bike card ownership	Yes	54.7(547)
		No	45.3(453)
Travel mode	Main mode of travel	Driving	12.4(124)
		Riding	29.8(298)
		Walking	43.8(438)
		Public transport	10.9(109)
		Taxis	3.1(31)

In the descriptive analysis, the age range of the respondents was 18 to 35 years old, and the majority of university students were in the age group of "18 to 26", accounting for 92.4%. In terms of education status, 40.6% of the respondents had a bachelor's degree. In terms of income, respondents' income covers the living expenses (unit of measurement: Chinese Yuan) given by their families, and most of them are in the range of "2000 to 3000" (33.7%) and "3000 to 4000" (40.6%).

2.3 Active travel tendency

To determine the tendency of active travel among university students, the question "Do you tend to walk or ride in your daily travel" was set as binary variables, "0" means no, "1" means yes. The questionnaire was supplemented with the question "How many days have you chosen to walk or ride in the last 14 days? " This is used as a reference for respondents to choose whether they have a tendency to travel actively or not. The results of our survey show that nearly one-third (62.8%) of the respondents have a tendency to travel actively, which illustrates the restricted travel pattern in closed university campuses in China.

2.4 Measurement of Green Space

2.4.1 Green View Index

GVI refers to the proportion of greenery in the landscape. It was found that GVI can reflect the green environment at the human eye level. People can get a more comfortable view when the green visual ratio is between 15% and 25% (Yoji Aoki, 1987). The data collection method used in this study was referenced from a previous study by Ye et al. (2019). The sample points of street-view images along the road network of six universities in Haidian District, Beijing at 50m intervals were selected in ArcGIS 10.8 (Figure 1). At each point, street view images can be captured in four directions and the street view image data are captured using the Baidu Maps API platform.

However, this study is based on the assumption that there are no significant time-varying green features at the street level, due to availability, this study extracts information from the street view image data from 2017. The principle of calculating the green visual rate used in this study is a pixel-width image segmentation method based on convolutional neural networks. Based on the ResNet framework (Wu et al., 2019), image segmentation was performed using ADE20k dataset to classify the street view images (Zhou et al., 2019). The trees in the field of view as well as vegetation such as grass are identified in the model training to calculate the green view index. The GVI data of six universities in Beijing Haidian District were obtained based on the calculated results. A sample of the analysis of the street view image by applying the ResNet algorithm is shown in Figure 2.

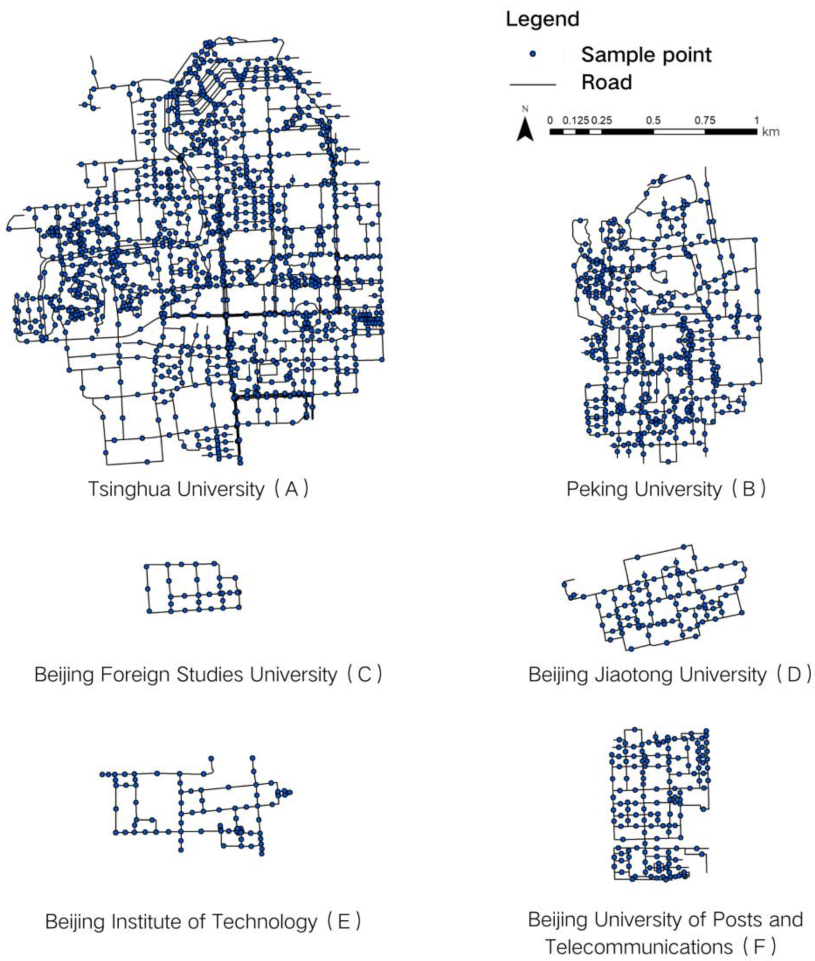

Figure 1. Sample points of street-view images

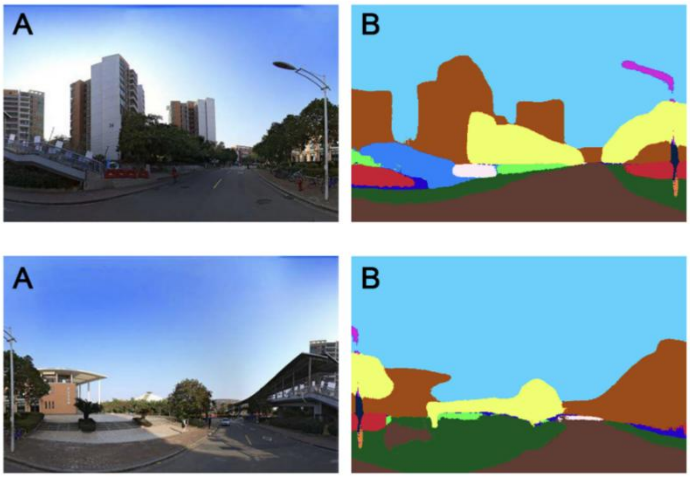

Figure 2. Process sample analysis by image segmentation (A. original images; B. Processed results)

The GVI is calculated as the ratio of green vegetation pixels to total pixels in four images per point:

$$V_i = \frac{\sum_{j=1}^{4} G_{ij}}{\sum_{j=1}^{4} T_{ij}}$$

where V_i refers to the GVI of point i, G_{ij} refers to the green pixels in the j th image at point i, and T_{ij} refers to the total pixels in the j th image at point i.

2.4.2 Remote sensing data

It has been shown that NDVI is a good indicator of vegetation cover and can be used for cross-regional comparative studies (Rhew et al., 2011; Markevych et al., 2017). NDVI is obtained from the red band (Red, band 4) and near infrared band (NIR, band 5) recorded by the Sentinel-2 satellite. The dataset COPERNICUS/S2_CLOUD_PROBABILITY used S2cloudless algorithm to remove most of the clouds (Rewehel et al., 2022), and used the NDVI normalization processing calculation tool to obtain the NDVI value data and its distribution. The resolution is 10 m × 10 m. The NDVI is calculated by dividing the difference between the reflectance in the NIR band and the reflectance in the red band in the remote sensing image by the sum of the two:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

NDVI ranges from - 1 ~ 1, and the higher the value, the higher the vegetation cover. For negative grids, this study used the grid calculator tool in ArcGIS 10.8 software to convert negative grids in remotely sensed images to 0 (Klompmaker et al., 2018a; Reid et al., 2018).

2.5 Control variables

Sociodemographic information included gender, age, education, income, household status, and marital status. Gender is a dummy variable that takes the value of 1 if the respondent is "male" and 0 for "other". Age refers to the current age at the time of applying the questionnaire. Education is measured by a dummy variable, with 0 being "undergraduate", 1 being "postgraduate", 2 being "Doctor and above ", and 3 means "Specialist and below". Household status indicates whether the respondent has a local household, and is represented by a dummy variable, with 1 indicating "local household" and 0 indicating "other". Marital status is represented by a dummy variable, with 1 indicating "with spouse" and 0 indicating "other". In addition to socioeconomic characteristics, transport abilities and travel mode were also included in the model to control for the effect that transport abilities and travel mode might have on the willingness to travel at low carbon levels. Respondents were asked whether they had a driver's license, private car, bicycle, E-bike and shared bike card, as well as their main mode of travel and travel satisfaction, which were classified on five levels according to the psychological ladder theory, with 0 indicating "very dissatisfied" 1 indicating 0 means "very dissatisfied", 1 means "dissatisfied", 2 means "average", 3 means "satisfied", and 4 means "very satisfied".

2.6 Statistical Analysis

Because of the hierarchical structure of the data in this study, multilevel logistic regression was used to examine the association between green space and active travel tendency of university students, with the following specification for the analysis (Goldstein, 2010):

$$\log\left(\frac{P_{ijk}}{1-P_{ijk}}\right) = \delta_0 + \alpha X_{ijk} + \beta Z_{jk} + \gamma C_k + \mu_j$$

The above equation shows the probability of AT intention $P(y_{ijk} = 1)$ of individual i in university j in city k, X_{ijk} represents individual-level variables, Z_{jk} represents university-level variables, and C_k represents city-level variables. α, β, and γ are the corresponding coefficients, and μ_j is the random effect of unobserved factors at the university level, $\mu \sim N(0, \sigma_\mu^2)$.

In the model, individuals at level 1 are nested within neighborhoods at level 2. This study used a stepwise approach to test the effect of GVI on respondents' propensity to travel actively. First, this study estimated the association between covariates and respondents' propensity to travel actively (Model 1). Second, this study added independent variables (GVI and NDVI) to Model 1 and reran the regression (Model 2) to explore the relationship between green space and active travel among college students. Finally, previous studies have shown that transportation travel characteristics are associated with the propensity to travel actively (Zhong et al., 2019), so the effect of green exposure on active travel may be influenced by other personal travel characteristics. Therefore, this study added the transportation travel characteristics of college students (Model 3), such as travel patterns and travel satisfaction, to Model 2 to further consider the effect of green space on active travel of college students. The variance inflation factor (vif < 4) indicates that the covariance of different variables is acceptable in this study. Analyses were conducted using Stata 16 (StataCorp., College Station, TX, USA) using the "meologit" command.

3. Results

Table 2 shows the results of the multilevel logistic models. In this study, the demographic data from model 1 were regressed. A statistically significant positive relationship between marital status and university students' tendency to travel actively was found in model 1 (Coef. = 0.793, SE = 0.249). In terms of built environment, campus size had a positive effect on university students' tendency to travel actively (Coef. = 0.006, SE = 0.002).

Next, the independent variable (GVI and NDVI) was added to Model 1 for the regression (Model 2). As expected, green space was significantly positively associated with active travel tendency (Coef. = 0.150, SE = 0.062), however, this study did not observe an association between NDVI and univeristy students' propensity to travel actively. The result of Model 2 also indicate that the propensity to travel actively is high among university students who own bicycles and e-bikes, where the probability of active travel is roughly twice as high among students who own e-bikes as among students who own bikes (Coef. = 2.199, SE = 0.189). Students with Shared bike cards significantly used shared bicycles more frequently and had a significant contribution to active travel (Coef. = 0.388, SE = 0.174).

Finally, Model 2 was regressed with the addition of traffic trip characteristics as a reference (Model 3) and Model 3 had the lowest AIC score (954.091). In the best-fit model Model 3, green space also showed a stable positive effect on active travel (Model 2: Coef. = 0.150, SE = 0.062; Model 3: Coef. = 0.160, SE = 0.072). Similarly, as in model 2, this study found that transport ownership, such as E-bike, Bike and Shared bike card ownership, was also associated with the propensity to travel actively. With respect to the transport characteristics of university students, students who walked as their primary mode of daily travel showed a higher tendency to actively travel relative to those who drove as their primary mode of daily travel (Coef. = 0.903, SE = 0.417), and was statistically significant (p value < 0.05). Surprisingly, the results of this study did not find any association between travel satisfaction (i.e. biking satisfaction and walking satisfaction) and the trend of active travel among university students, which challenges the previous study (De and J,2019).

Table 2 Baseline Model

	Model 1 Coef. (S.E.)	Model 2 Coef. (S.E.)	Model 3 Coef. (S.E.)
Independent variables			
GVI		0.150** (0.062)	0.160** (0.072)
NDVI		-0.035 (0.152)	-0.075 (0.201)
Demographic variables			
Female (ref: male)	-0.029(0.171)	-0.028 (0.171)	-0.047 (0.175)
Age (ref: under 18)			
18 - 20	0.758* (0.454)	0.776* (0.455)	0.591 (0.501)
21 - 23	0.588 (0.473)	0.610 (0.474)	0.411 (0.524)
24 - 26	0.948* (0.487)	0.959** (0.487)	0.695 (0.544)
> 26	0.610 (0.646)	0.639 (0.648)	0.735 (0.718)
Education Attainment (ref: specialties and below)			
Undergraduate	0.029 (0.196)	0.030 (0.196)	0.029 (0.199)
Postgraduate	-0.922*** (0.279)	-0.950*** (0.279)	-0.969*** (0.283)
Doctor and above	-1.170* (0.634)	-1.200* (0.632)	-1.371** (0.630)
Income level (ref: <2000 RMB per month)			
2000~3000 RMB per month	-0.113 (0.356)	-0.097 (0.356)	-0.232 (0.363)
3000~4000 RMB per month	0.123 (0.362)	0.157 (0.363)	0.060 (0.368)
Above 4000 RMB per month	0.132 (0.404)	0.176 (0.404)	-0.014 (0.410)
Local hukou (ref: non-local hukou)	-0.334* (0.186)	-0.351* (0.187)	-0.374** (0.189)
Partner relationship (ref: no partner relationship)	0.793*** (0.249)	0.777*** (0.249)	0.865*** (0.253)
Campus Area (hm2)	0.006***(0.002)	0.003 (0.002)	0.003 (0.002)
Travel characteristics			
Driving licence (ref: no driving licence)	0.133 (0.172)	0.130 (0.172)	0.090 (0.178)
Car ownership	-0.240 (0.249)	-0.242 (0.248)	-0.323 (0.300)
E-bike ownership	2.201*** (0.190)	2.199*** (0.189)	2.153*** (0.318)
Bike ownership	0.501*** (0.181)	0.521*** (0.182)	1.119*** (0.347)
Shared bike card ownership	0.393** (0.174)	0.388** (0.174)	0.367** (0.186)
Travel mode (ref: driving)			
Riding			-0.061 (0.474)
Walking			0.903** (0.417)
Public transport			0.693* (0.390)
Taxis			0.501 (0.581)
Walking satisfaction (ref: low walking satisfaction)			-0.085 (0.170)
Riding satisfaction (ref: low			0.169 (0.126)

riding satisfaction)			
Driving satisfaction (ref: low driving satisfaction)			0.090 (0.102)
Public transport satisfaction (ref: low public transport satisfaction)			-0.145 (0.194)
Taxi satisfaction (ref: low taxi satisfaction)			0.101 (0.091)
Constant	-2.601*** (0.701)	-6.176*** (1.837)	-6.276*** (2.429)
Random Part			
Var(_cons[school])	0.446 (0.299)	0.156 (0.120)	0.214 (0.162)
Number of individuals	1000	1000	1000
Number of schools	6	6	6
AIC	956.870	955.428	954.091

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

4. Discussion and Conclusion

4.1 Discussion

Regarding the two green space measurements, NDVI is usually (but not always) observed from space and is somewhat of an inaccurate measure of the Green View (GVI) at the human eye level. However, only the greenery visible from the pedestrian's perspective can influence or reflect the pedestrian's experience of green exposure (Li et al., 2015). In this study, green spaces were analyzed from street-view images, showing that exposure to green spaces was statistically significant and positively associated with university students' tendency to participate in AT after controlling for individual socio-demographic and transport characteristics. These findings confirm the results of previous studies (Astell-Burt et al., 2014; Lu et al., 2019b).

The study also found that there was a greater propensity to travel actively for university students whose primary mode of travel was walking. Also, driving has a tendency to inhibit active travel and other modes of travel are less associated with active travel, which may also be due to the fact that the primary mode of travel used on university campuses is walking. This study also found that transportation ownership (e.g., bicycles and e-bikes) can significantly contribute to students' tendency to travel actively. It is conceivable that personal ownership of a bicycle or e-bikes would facilitate active travel, and e-bikes tend to be more convenient, faster, and more comfortable than bicycles, making the propensity to actively travel stronger for students who own e-bikes.

In terms of other variables, respondents with a master's degree have a significantly higher propensity to travel actively compared to students with a specialist degree. This result may be due to the fact that students with master's degree are more willing to travel actively due to their research tasks, job search and internship, and the fact that they have already developed active travel habits.

4.2 Conclusion

Based on the association between green space and active travel, this study used street-view images, survey data and multilevel logistic regression models to explore the relationship between green space and active travel behavior of university students in a closed university campus. This study examined the influence of green space on active travel on six university campuses in Beijing, using university students in the formative stage of travel behavior. This study applied multiple techniques to measure green space, including deep learning image segmentation of street-view images and extraction of green space from satellite remote sensing images. The result of this study show that green space had a significant effect on physical activity of university students. This study also found that the private ownership of bicycles and e-bikes and the popularity of shared bicycles are conducive to active travel. Transportation is one of the key areas of carbon emission in China, and promoting its comprehensive green and low-carbon transformation is the key to promoting high-quality development of transportation. The 14th Five-Year Plan for Green Transportation proposes to promote the integration of green transportation and intelligent transportation, and to promote low-carbon travel habits among young people, which is particularly important for the future layout of green transportation.

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