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# Urban Forestry & Urban Greening



journal homepage: www.elsevier.com/locate/ufug

# A quasi-experimental study on the impact of park accessibility on the mental health of undergraduate students

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#### ARTICLE INFO

Handling Editor: Dr Cecil Konijnendijk van den Bosch

Keywords: Causality Green space Mental health Modifiable areal unit problem Difference-indifference model Propensity score matching

### ABSTRACT

Public mental health issues have gained growing attention from academics and policymakers due to their increasing prevalence and multiple adverse and severe consequences. Although some studies have supported the benefits of parks on mental health, the causal relationship between park accessibility and mental health remains unclear. By converting a large cross-sectional sample of 22,060 undergraduates nationwide in China into a quasipanel dataset, this study untangled the causal impact of park accessibility on mental health benefits. We employed a quasi-experimental research design and used a difference-in-difference (DID) model to estimate the causal effects of park accessibility on depression symptoms within varying buffer sizes (i.e., 0.5 km, 1 km, 1.5 km, and 2 km). Furthermore, propensity score matching (PSM) and the Heckman selection model were employed to mitigate the selection bias caused by the prior differences of the treatment group and the control group. The results revealed that park accessibility had a positive effect on mental health and that its influence decreased with increased buffer sizes. Regarding the gender and living-cost differences, park accessibility within the 0.5 km and 1 km buffers had a greater mental health impact on females than on males, and it had a greater impact on high-living cost undergraduates than on low-living cost undergraduates. To increase the mental health benefits of undergraduate students, this study suggests that the provision of parks within a 1 km radius buffer surrounding the campus should be a priority to improve the mental health of undergraduates.

### 1. Introduction

Mental health issues and disorders, such as depression and anxiety, are a growing public health concern worldwide (WHO, 2017) and are expected to become the leading cause of disease burden by 2030 (Ferrari et al., 2013). Moreover, they may lead to many physical diseases, e.g., cardiovascular disease (Li et al., 2020), metabolic syndrome (Pan et al., 2012), tooth loss (Okoro et al., 2012), diabetic complications (de Groot et al., 2001) and spinal cord injury (Krueger et al., 2013). Hence, policymakers and public health officials have paid increasing attention to public mental health (Department of Health, 2010).

Green space, as an indispensable component of the urban environment, plays a crucial role in promoting mental health (Hartig et al., 2014). The potential underlying mechanisms include reducing mental stress (Kaplan, 1995; Ulrich et al., 1991), stimulating physical activity (Dzhambov et al., 2018; Liu et al., 2019), and enhancing social cohesion (de Vries et al., 2013). The effects of green space may be more pronounced among some population subgroups than others (Hartig et al., 2014). Most such empirical studies focus on the elderly (Dzhambov and Dimitrova, 2014; Helbich et al., 2019) and children (Putra et al., 2021). For instance, green spaces can protect the elderly against depression (Helbich et al., 2019) and contribute to mental health among children (Putra et al., 2021). Unlike children and elderly individuals, undergraduate students are not regarded as vulnerable groups; therefore, little attention has been given to this group. However, depression is a common problem among university students (Ibrahim et al., 2013; Auerbach et al., 2018). According to a systematic review, 30.6 % of university students have depressive disorders, which is considerably higher than the rates reported for the general population (Ibrahim et al., 2013).

Although there is consensus regarding the mental health benefits of

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https://doi.org/10.1016/j.ufug.2023.127979

Received 7 November 2022; Received in revised form 12 April 2023; Accepted 29 May 2023 Available online 31 May 2023 1618-8667/© 2023 Published by Elsevier GmbH. green spaces, there are three major research gaps. First, few studies have focused on undergraduate students when considering the mental health outcomes of green spaces. Second, few studies have established the causality of the green spaces-health relationship (Hartig et al., 2014). Evidence has largely been acquired using a cross-sectional research design, which has inherent methodological limitations (e.g., residential selection bias) to infer causality. Third, the heterogeneity in the mental benefits of green spaces across geographical scales and subgroups has often been omitted, such as the modifiable areal unit problem (MAUP) and gender- and socioeconomic status (SES)-related diversities.

In this study, we aimed to bridge these research gaps by utilizing a quasi-experimental approach to evaluate the robust link between park accessibility and undergraduates' mental health. Specifically, we capitalized on the unique characteristics of Chinese undergraduate students, who possess limited freedom in selecting their residential locations, because most of them reside in dormitories on the university campus (Li et al., 2015; Yang et al., 2022). Their year in university reflect how long they have been exposed to the campus built environment. Consequently, we transformed cross-sectional data into quasi-panel data, enabling us to apply the difference-in-differences (DID) model for estimating causality. Then, we applied the Heckman selection model and the PSM method to avoid the bias caused by the prior differences between the treatment group and the control group, including residential self selection bias. Furthermore, we dealt with the MAUP by applying diverse buffer sizes (i.e., 0.5 km, 1 km, 1.5 km, and 2 km). Regarding the potential moderating effect of gender and living costs, we further analyzed the effect of park accessibility in the stratified groups. Additionally, we further discuss the potential pathways through which parks influence mental health.

### 2. Literature review

## 2.1. Health impacts of parks on mental health

Parks provide leisure and recreation, meet social needs, offer visual and psychological relief, and contribute to the quality of life of individuals (Loukaitou-Sideris, 1995). Thus, it is an essential component of good city form (Lynch, 1981). Specifically, parks have restorative benefits that promote mental health. According to stress reduction theory (STR), green space reduces mental stress and evokes positive emotional states and physiological markers (Ulrich et al., 1991). Attention restoration theory (ART) suggests that exposure to nature helps divert attention and lead to recovery from fatigue (Kaplan, 1995). In this vein, parks, as a common type of natural environment, have a restorative effect on mental health (Ojala et al., 2019). The longer duration of stay in the parks, the more restorative benefits that individuals could receive (Li et al., 2019).

Here, we address health impacts of parks on mental health through two potential pathways: cycling and sleep quality. Cycling is one of the common forms of physical activity in China. The proximity of parks is positively associated with cycling (Li et al., 2021). Parks often attract leisure cycling behavior (Guo et al., 2022; Mateo-Babiano et al., 2016). Meanwhile, cycling as a form of moderate to vigorous physical activity is linked to better mental health (Wolf and Wohlfart, 2014; Garrard et al., 2021), because cycling can prevent anxiety and depression, improve cognitive functioning, and increase subjective well-being (Pucher and Ralph, 2012).

Sleep quality may also serve as a mediator in the relationship of parks and mental health. Sleep quality is a biologically-driven periodic state of mind that helps maintain mental health (João et al., 2018; Çelik et al., 2019). Parks can influence sleep quality through two mechanisms. Firstly, they may help mitigate the adverse effect of stress on sleep quality (Yang et al., 2020). Second, parks can contribute to better sleep quality by reducing noise levels (Koprowska et al., 2018). Prior research

has already demonstrated a link between parks and improved sleep quality and quantity (Shin et al., 2020).

### 2.2. Causality inferences

Although there is consensus on the benefits of parks on mental health, some limitations should be noted on the methodological aspect. Most studies have used cross-sectional research design, which makes it hard to infer any causal impact of contact with nature on health (Hartig et al., 2014). Cross-sectional data do not have time attributes; hence, it is difficult to establish causality (Frank et al., 2019; Jarvis et al., 2020; Roberts et al., 2021; Xie et al., 2022). Furthermore, residential self-selection bias is difficult to be avoided. Self-selection bias is mainly caused by non-randomly selected samples (Heckman, 1979). In the environment-behaviour context, it is related to the prior preference for activities intended in residential and visiting places with certain characteristics, rather than being randomly assigned (Li et al., 2019). In this vein, the observed association between green spaces and health outcomes can be confounded by self-selection bias and consequently explained by individual factors (Handy et al., 2006).

Thus, some studies have employed a quasi-experimental approach to address endogeneity arising from unmeasured confounders and to infer causality (Branas et al., 2011; Xie et al., 2021, 2022). In certain cases, implementing an experimental design may be unethical or impractical due to the random assignment and direct manipulation of variables. Quasi-experimental designs provide a more viable alternative for drawing causal inferences (Xie et al., 2021, 2022). By comparing the outcomes of a treatment group and a control group before and after an intervention, it rules out unobserved and time-invariant confounding factors that may be correlated with both the treatment and the outcome variable (Branas et al., 2011; Peter et al., 2012).

### 2.3. Heterogeneity

Some factors may moderate the impact of park accessibility on mental health. First, the influence of green space may be confounded by MAUP and vary with buffer size. For example, Coombes et al. (2010) demonstrated that the use frequency of green space decreased so that health risks increased with increasing distance from it within a 1600 m buffer. While Hillsdon et al. (2015) found that most physical activity took place outside of an 800 m buffer. Diverse buffer sizes represent different mechanisms underlying the health benefits of parks (Markevych et al., 2017).

Individual characteristics, such as gender- and SES-related diversities, may affect park use and moderate the health benefits of parks due to the differences in perception (Loukaitou-Sideris and Sideris, 2009; Ode Sang et al., 2016), social norms (Kavanagh et al., 2006), mobility and active spaces (Morency et al., 2011; Schwanen et al., 2015). First, the mental health benefits of parks may also differ with gender. Females are more concerned about safety (Branas et al., 2011). For example, parks with inadequate visibility or lighting might deepen females' sense of insecurity (Loukaitou-Sideris and Sideris, 2009). In addition, females may spend more time at home due to social norms, so their health status may be more influenced by their nearby residential environments (Kavanagh et al., 2006). Furthermore, females might receive more restoration effects from exposure to green space because they are more likely to appreciate the aesthetic value of green space (Ode Sang et al., 2016). Thus, some studies have found that green space is more beneficial for women's mental health (Xiao et al., 2021; Wolf and Wohlfart, 2014). However, some proven it is more beneficial for males (Jarvis et al., 2020). One possible reason is that males are more likely to use and, therefore, benefit more from public green spaces (Richardson and Mitchell, 2010).

Second, the mental health benefits of parks may also differ with SES

(Roberts et al., 2019). Most studies have found that public green spaces had a greater protective effect on disadvantaged groups, as they lacked access to other health-promoting resources and had a stronger dependency on proximate green space (Rigolon et al., 2021). Some believe that individuals with high SES are more likely to approach green spaces (Ravensbergen et al., 2016).

### 3. Methods

### 3.1. Study area and participants

Previous studies have pointed out that it is difficult to explore the causal relationship between green spaces and health outcomes with cross-sectional data. Thus, we chose undergraduate students as our research sample for two reasons. First, choosing undergraduate students in China prevents residential selection bias because they not only have little freedom to choose where they live (Li et al., 2015), but also study and live in the same place (Zhan et al., 2016; Yang et al., 2022). Meanwhile, Chinese undergraduates' choice of universities is rarely determined by campus environment, but by school education, familial expectations, choices of city and major, and the scores of the national college entry exams instead (Ashraf et al., 2017; You and Hu, 2013). Second, we can distinguish whether they were influenced by urban

parks by their grades to estimate the robust relationship between parks and mental health. Specifically, we finished the survey at the beginning of a new school year (from September 19 to 26, 2018). Hence, the freshmen were not influenced by the parks around the university campus at that time. In this vein, they can be regarded as the preintervention group. In contrast, from sophomore year and above, the students had been exposed to the green space around the university campus for at least one year; hence, they were deemed to be the postintervention group.

In this study, individual data were obtained via a nationwide survey conducted by the First Affiliated Hospital of Kunming Medical University in 2018 (ethical number: 2018-L-25). Demographic and socioeconomic attributes were collected via a self-report questionnaire, and health-related behaviours were collected via face-to-face interviews by professional medical practitioners from hospitals.

The participants were selected with a multiple-stage stratified sampling method. First, 29 provinces/municipalities (excluding Tianjin and Tibet) in mainland China were selected for this survey. Second, two to four campuses in each province/municipality were randomly selected. Third, according to the probability proportion of the undergraduate student population size, 300–700 undergraduate students on each campus were interviewed. Ultimately, a representative sample of 23,488 undergraduates from 90 campuses in 29 provinces was generated



Fig. 1. Spatial distribution and sample size of undergraduate students participating in this study.

### Table 1

Definitions and data sources of variables.

	Variables	Definition	Data source
Mental health	PHQ-9	The sum of PHQ-9 scores.	Survey
Park accessibility	Accessibility	If the distance to the park is within a circular buffer defined by thresholds, then Accessibility <sub>i</sub> is equal to 1; otherwise, 0	Amap in 2019 (https://lbs.amap.com/)
Socioeconomic demographic characteristics	Exposure	Exposure is a dummy variable. $Exposure_i = 1$ indicates sophomores and above (i.e., those who are influenced by green space). $Exposure_i = 0$ indicates freshmen (i.e., those who are not influenced by green space).	Survey
	Gender	A dummy variable. If the respondent is male, this variable $= 1$ , and it $= 0$ otherwise.	Survey
	Age	The respondent's age.	Survey
	Living costs	Undergraduate's monthly living expenditure level (more than 1000 and less than 1000 RMB).	Survey
	Marital status	A dummy variable. If the respondent has married, this variable $= 1$ , and it $= 0$ otherwise.	Survey
	Type of Hukou	A dummy variable. If the respondent's household registration is in an urban area, this variable $= 1$ and it $= 0$ otherwise.	Survey
	Ethnicity	A dummy variable. If the respondent is Han ethnicity, this variable $= 1$ , and it $= 0$ otherwise.	Survey
	Alcohol habit	A dummy variable. If the respondent is a drinker, this variable $= 1$ , and it $= 0$ otherwise.	Survey
	Smoking habit	A dummy variable. If the respondent is a smoker, this variable $= 1$ , and it $= 0$ otherwise.	Survey
	Sleep quality	A categorical variable. If the sleep quality of the respondents is very bad, this variable $= 1$ ; if the sleep quality is bad, this variable $= 2$ ; if the sleep quality is general, this variable $= 3$ ; if the sleep quality is good, this variable $= 4$ ; and if the sleep quality is very good, this variable $= 5$ .	Survey
Built environment features	Bus accessibility	If the distance to the nearest bus stop is within a circular buffer defined by thresholds (i.e., 0.5 km, 1 km, 1.5 km, and 2 km), then this variable is equal to 1, and it is 0 attermine	Amap in 2019
	Subway accessibility	If the distance to the nearest subway station is within a circular buffer defined by thresholds (i.e., 0.5 km, 1 km, 1.5 km, and 2 km), then this variable is equal to 1, and it is 0 otherwise.	Amap in 2019
	Population density	Population divided into 0.5 km, 1 km, 1.5 km, and 2 km buffer areas.	Worldpop in 2018, with the resolution of 100 * 100 m (https://www.worldpop. org/)
	Street intersections	Number of intersections within 0.5 km, 1 km, 1.5 km, and 2 km.	Open Street Map in 2018 (https://www. openstreetmap.org/)

(Fig. 1). After excluding missing values, our valid sample contained 22,060 respondents.

3.2. Dependent variables

The nine-item Patient Health Questionnaire was used to measure mental health status (PHQ-9, Kroenke et al., 2001). It has been widely used to measure the depression severity of nonclinical populations (Breedvelt et al. 2020; Yang et al., 2022). A higher score indicates more severe depression. Generally, a score of PHQ-9 less than 5 can be recognized as minimal or no depression (Kroenke et al., 2001). The data on mental health were collected via a structured questionnaire, which was completed by undergraduates with the assistance of healthcare professionals (Yang et al., 2022).

### 3.3. Independent variable

Many studies have tried to identify built environment factors, which may influence park use. These factors include physical distance to parks (Cohen et al., 2006), perceived distance to parks (Park, 2017), park features (Cohen et al., 2006; Veitch et al., 2020), and park qualities (Zhang et al., 2013). Among them, accessibility has been proven to be a quantifiable and powerful concept for both research and practice (Handy and Niemeier, 1997; Handy, 2020).

The variable of concern is the interaction term of a dummy variable (*Exposure*<sub>i</sub>) indicating whether an undergraduate is influenced by the environment and another dummy variable indicating the park accessibility. Detailly, we deemed that *Exposure*<sub>i</sub> is equal to 1 if the individual is sophomore and above. We used park proximity, namely, physical distance from the park, as the proxy of park accessibility (Eq. 1). Consider an undergraduate residing at point *i* with the closest park at *j*. If the distance to the park, *distance*<sub>ij</sub>, is within a distance threshold of D (i.e.,

0.5 km, 1 km, 1.5 km, and 2 km, respectively, in this study), then *Accessibility*, is equal to 1; otherwise, 0:

$$Accessibility_i = \begin{cases} 1, distance_{ij} \le D\\ 0, distance_{ij} > D \end{cases}$$
(1)

The variable of concern was the interaction term (*Accessibility*<sub>*i.d.*</sub> \* *Exposure*<sub>*i*</sub>) indicating whether undergraduate i is influenced by park accessibility.

### 3.4. Controlling variables

Mental health outcomes were also affected by individual factors and built environment features. Following previous studies, we collected the following individual factors: age (White et al., 2013; Wu et al., 2020), gender (White et al., 2013; Yigitcanlar et al., 2020), living costs (Yigitcanlar et al., 2020; Wu et al., 2020; Yang et al., 2022), marital status (White et al., 2013; Yigitcanlar et al., 2020; Li et al., 2019), ethnicity (Helbich, 2019; Yang et al., 2022), alcohol consumption habits (Liu et al., 2019; Wang et al., 2019), smoking habits (Liu et al., 2019; Wang et al., 2019), sleep quality (Çelik et al., 2019), and the type of Hukou, which refers to permanent residency rights in a local area and influences many associated social welfare and government-provided services. (Liu et al., 2019; Yang et al., 2022).

In addition, mental health may be affected by the features of the local built environment (Wu et al., 2020). In this study, we measured subway accessibility (Wu et al., 2020), bus accessibility (Yang et al., 2022), population density (Liu et al., 2019; Wu et al., 2020; Yang et al., 2022) and road intersections (Yang et al., 2022) within a 1000 m radius buffer around the centroids of each campus, which is a widely accepted distance for walking instead of driving or using other motorized transportation modes (Millward et al., 2013). Definitions and data sources are listed in Table 1.

### 3.5. Descriptive statistics

After excluding missing data, a sample of 22,060 undergraduates matched the built environment data. Table 2 shows the descriptive statistics for the freshmen, the sophomores and above, and all undergraduates. Specifically, the average PHQ-9 score of the freshmen was lower than that of the sophomores and above (4.7 vs. 5.2). On average, the freshmen were 18.5 years old (SD =  $\pm$  1.2), and the sophomores and above were 20.6 years old (SD =  $\pm$  1.6). Overall, 44.4 % were male undergraduates. In addition, almost half of the students (50.2 %) received more than 1000 yuan living costs from their parents. All the variables had a VIF value of no more than 5 (Supplementary B).

### 3.6. Data analysis

i

To explore the relationship between mental health and park accessibility, we conducted quasi-experimental research using a crosssectional dataset. Despite we did not know what freshmen have been exposed to in the last 12 months have been, it is obvious that they were not influenced by the campus environment. Because we collected the data at the beginning of a new school year (from September 19 to 26, 2018) when the freshmen just enrolled in school. Thus, the freshmen were assumed as the pre-intervention group because they had not been exposed to the campus park environment, while sophomores and above were assumed as the post-intervention group because they had been exposed to the campus park environment for more than one year. The assumption was verified by comparing the impact of park accessibility at various buffer sizes among the freshmen and sophomores and above (see Supplementary A). The results in Supplementary A confirm our assumption. The campus park accessibility did not affect the mental health of those who were not influenced by the campus environment (i. e., freshmen) but had a significant negative impact on mental health among those who were influenced by the campus environment (i.e., sophomores and above).

Hence, we first categorized the undergraduate students into two groups according to whether they were influenced by parks: those exposed to the environment (sophomore and above,  $Exposure_i = 1$ ) and those who were not (freshmen,  $Exposure_i = 0$ ). Then, we divided these two groups of college students into four groups based on whether parks were accessible with a certain buffer. We regarded college students who had access to parks within a certain buffer as the treatment group, while those who had no access to parks were regarded as the control group. Thus far, we have satisfied the research framework of the DID method. The following DID models were constructed in Eq. (2):

$$PHQ9_{i} = \beta_{0} + \beta_{1}Accessibility_{i,d}$$

$$* Exposure_{i} + \beta_{2}Exposure_{i} + \beta_{3}Accessibility_{i,d} + \sum_{j} \tau_{j} * X_{ji} + \varepsilon_{i}$$
(2)

where  $PHQ9_i$  represents the PHQ9 score of respondent *i*. Accessibility<sub>*i*,*d*</sub> is a dummy variable: if the distance from the location of respondent *i* to the nearest park was within the radius buffer *d* (i.e., 0.5 km in Model 1, 1 km in Model 2, 1.5 km in Model 3, and 2 km in Model 4), Accessibility<sub>*i*,*d*</sub> = 1; otherwise, Accessibility<sub>*i*,*d*</sub> = 0.  $X_{ji}$  is the matrix vector of the control variables, and  $\varepsilon_i$  is the stochastic disturbance term.

To further examine the dose—response effect, park accessibility was measured as a graded variable (Xie et al., 2021). Specifically, *Accessibility* = 1 when the closest park is within 0.5 km from the centroid of a campus; *Accessibility* = 2, 3, 4 and 5 when the closest park is within 0.5–1 km, 1–1.5 km, 1.5–2 km, and more than 2 km, respectively. Model 6 was also constructed based on the DID model, where the coefficient of the interaction term *Accessibility<sub>i,d</sub>* \* *Exposure<sub>i</sub>* indicated the dose—response effect of park accessibility.

Accounting for within-groups correlated homogeneity errors caused by both within-campus and city homogeneity (Huang and Li, 2022), all

### Table 2

Characteristics of respondents and built environment.

Variables (units)	Freshmen proportion/ mean (SD)	Sophomore and above proportion/	All samples proportion/ mean (SD)
		mean (SD)	
PHQ9 score (numeric)	4.7 (4.3)	5.2 (4.5)	5.1 (4.5)
The distance to the nearest park is within	17.3 %	17.0 %	17.1 %
The distance to the nearest park is more than 0.5 km	82.7 %	83.0 %	82.9 %
Park_1000 (%) The distance to the nearest park is within	36.4 %	45.0 %	42.7 %
1 km The distance to the nearest park is more than 1 km	63.6 %	55.0 %	57.3 %
Park_1500 (%) The distance to the nearest park is within	57.8 %	68.2 %	65.4 %
The distance to the nearest park is more than 1.5 km	42.2 %	31.8 %	34.6 %
Park_2000 (%)			
The distance to the nearest park is within 2 km	77.9 %	85.2 %	83.3 %
The distance to the nearest park is more than km	22.1 %	14.8 %	16.7 %
Gender (%) Male	439%	44.6 %	44 4 %
Female	56.1 %	55.4 %	55.6 %
Age (numeric)	18.5 (1.2)	20.6 (1.6)	20 (1.7)
Living costs (%)		51 5 0/	50.0.0
less than 1000 Yuan	46.5 % 53.5 %	51.5 % 48.5 %	50.2 % 49.8 %
Marital status (%)			
Married	0.2 %	0.5 %	0.4 %
Type of Hukou (%)	99.0 %	99.3 %	99.0 %
urban Hukou	59.1 %	61.1 %	60.6 %
rural Hukou	40.9 %	38.9 %	39.4 %
Ethnicity (%)	96.0.04	96 9 04	96 6 04
the other	14.0 %	13.2 %	13.4 %
Alcohol (%)			
Being a drinker	35.4 %	40.7 %	39.3 %
Smoking (%)	64.6 %	59.3 %	60.7 %
Being a smoker	2.8 %	4.0 %	3.7 %
Not a smoker	97.2 %	96.0 %	96.3 %
Sleep quality (%)	0.0.0/	1.0.0/	1.0.0/
Very Dad Bad	0.9%	1.3 %	1.2 %
General	40.6 %	43.8 %	42.9 %
Good	34.3 %	32.5 %	33.0 %
Very good	19.1 %	16.5 %	17.2 %
Bus accessibility (%) The distance to the nearest bus stop is within 0.5 km	84.5 %	87.0 %	86.3 %
The distance to the nearest bus stop is within 1 km	98.3 %	98.2 %	98.2 %
The distance to the nearest bus stop is within 1.5 km	98.3 %	98.2 %	98.2 %
The distance to the nearest bus stop is	98.3 %	98.2 %	98.2 %

(continued on next page)

within 2 km

#### Table 2 (continued)

Variables (units)	Freshmen proportion/ mean (SD)	Sophomore and above proportion/ mean (SD)	All samples proportion/ mean (SD)
Subway accessibility (%)			
The distance to the nearest subway station is within 0.5 km	18.7 %	24.20 %	22.7 %
The distance to the nearest subway station is within 1 km	40.3 %	47.90 %	45.9 %
The distance to the nearest subway station is within 1.5 km	47.3 %	53.50 %	51.8 %
The distance to the nearest subway station is within 2 km	52.8 %	56.60 %	55.6 %
Population density			
(people·km2)			
0.5 km buffer	687,494	870,870.5	821,759.5
	(823,865.2)	(880,965.2)	(869,822.6)
1 km buffer	789,772.7	1,074,058.9	997,922.8
	(955,737.2)	(1,060,532.2)	(1,041,126.9)
1.5 km buffer	712,954.2	963577.3	896,456.7
	(887,352.8)	(999404.3)	(976,968.9)
2 km buffer	699,907.9	952,422.9	884,795.6
	(874,785.9)	(1,007,672.9)	(980,242.8)
Intersections			
(number·km2)			
0.5 km buffer	6.7 (5.7)	9.2 (11.4)	8.5 (10.2)
1 km buffer	27.5 (20.2)	37 (35.6)	34.5 (32.5)
1.5 km buffer	61.6 (45.6)	82.7 (74.4)	77.1 (68.5)
2 km buffer	111.4 (80.7)	145.9 (126.4)	136.6 (116.9)
Number of individuals	5908	16,152	22,060

the regressions were based on these two clustering dimensions. Specifically, the standard error adjusted for 90 clusters on campuses, and 44 clusters in cities. Graphic displays of the critical variable (i.e., the interaction terms of whether exposure to the built environment and park accessibility) were presented in the following text, and more information was presented in Supplementary C1–3 in a tabular form. Additionally, the results clustering campuses alone were also provided in Supplementary D1–3. All of the analyses were estimated with robust

standard errors conducted by Stata 15.0.

### 4. Results

## 4.1. Effect of park accessibility on mental health

We adopted DID models to estimate the relationship between park accessibility and mental health with various distance buffers in Fig. 2. The significant interaction terms in 0.5 km and 1 km buffers demonstrated that park accessibility had a significantly negative effect on the PHQ9 score within the 0.5 km and 1 km buffers, respectively. It is noteworthy that the magnitude of the effect size decreases with increased buffer size. However, park accessibility has no significant impact on the PHQ9 score within the 1.5 km buffer or the 2 km buffer, respectively.

To further examine the dose—response effect of park accessibility, we measured park accessibility as an ordered variable. The result suggests that being further away from a park is associated with higher levels of depression.

### 4.2. Heterogeneity analysis

Fig. 3 reveals the results stratified by gender. Park accessibility significantly and negatively influenced both at the males and females in the 0.5 km and 1 km buffers, and its effect size decreased with increased buffer size. Furthermore, park accessibility had a larger effect size on the females than on the males.

We also performed heterogeneity analyses based on living cost (see Fig. 4). The results demonstrated that access to parks had significant negative impacts on the mental health of those with high and low living costs within the 0.5 km and 1.0 km buffers. Furthermore, the effect size of park accessibility was larger in the high-living cost group than in the low-living cost group.

### 4.3. Robustness check

### 4.3.1. Residential selection bias

People are not randomly assigned where they live because of individual preferences. In this study, we focused on the undergraduates who have little freedom in selecting residential locations to mitigate this bias.



Fig. 2. The impact of park accessibility on mental health within the 0.5 km, 1 km, 1.5 km, and 2 km buffers.



Fig. 3. The heterogeneous effect of being male and female on mental health.



Fig. 4. The heterogeneous effect of low and high living costs on mental health.

Regarding the university selection might be influenced by individual preferences as well, we applied the Heckman selection model to avoid residential selection bias (Maddala, 1986; Li et al., 2022).

First, we applied probit regression to analyse the residential choices in whether exposure to parks and estimated the inverse Mill's ratio. The dependent variable in the first stage indicated whether the undergraduates influenced by the park accessibility within diverse buffer sizes. And the independent variables comprised an exogenous variable and socioeconomic demographic characteristics, such as gender, age, living costs, marital status, type of hukou, ethnicity, alcohol habit, smoking habit, and sleep quality. Specifically, we selected the location of the campus as the exogenous variable. Because the location of the campus may associate with the campus environment but cannot directly influence the mental health of undergraduates. If the campus is located in the urban area, it is equal to 1, otherwise 0. The following Probit models were constructed in Eq. (3):

$$Accessibility_{id} - Exposure_i = \alpha_0 Urban_i + \sum \alpha_j * SES_{ji} + \varepsilon_i$$
(3)

where *Accessibility<sub>id</sub>\_Exposure<sub>i</sub>* represents whether respondent *i* has been influenced by park accessibility. *d* refers to the radius buffer (i.e., 0.5 km, 1 km, 1.5 km, and 2 km). *Urban<sub>i</sub>* is an exogenous variable. *SES<sub>ji</sub>* is the matrix vector of socioeconomic demographic characteristics, and  $\varepsilon_i$  is the stochastic disturbance term.

The computation of the inverse Mill's ratio was as follows Eq. (4):

$$IMR_{id} = \begin{cases} \frac{\varphi(\widehat{a_0}Urban_i + \sum \widehat{a_j} * SES_{ji})}{\Phi(\widehat{a_0}Urban_i + \sum \widehat{a_j} * SES_{ji})}, ifAccessibility_{id}.Exposure_i = 1\\ \frac{-\varphi(\widehat{a_0}Urban_i + \sum \widehat{a_j} * SES_{ji})}{(1 - \Phi(\widehat{a_0}Urban_i + \sum \widehat{a_j} * SES_{ji}))}, ifAccessibility_{id}.Exposure_i = 0 \end{cases}$$
(4)

where  $\Phi(.)$  refers to Cumulative Distribution Function, and  $\varphi(.)$  refers to Probability Density Function.

Then, we controlled the inverse Mill's ratio in equation (3) to determine the impacts of park accessibility within various buffers. The following DID models were constructed in Eq. (5):

$$PHQ9_{i} = \alpha_{0} + \alpha_{1}Accessibility_{id} * Exposure_{i} + \alpha_{2}Exposure_{i} + \alpha_{3}Accessibility_{id} + \alpha_{4}IMR_{id} + \sum_{j} \tau_{j} * X_{ji} + \varepsilon_{i}$$
(5)

where *PHQ9*<sub>i</sub> represents the PHQ9 score of respondent *i*. Accessibility<sub>id</sub> is a dummy variable: if the distance from the location of respondent *i* to the nearest park was within the radius buffer *d*, Accessibility<sub>id</sub> = 1; otherwise, Accessibility<sub>id</sub> = 0. X<sub>ji</sub> is the matrix vector of the control variables, *IMR<sub>id</sub>* is the inverse Mill's ratio calculated by Eq. (4), and  $\varepsilon_i$  is the stochastic disturbance term.

Fig. 5 reports the impact of park accessibility on mental health with the Heckman selection model within the 0.5 km, 1 km, 1.5 km, and 2 km buffers, respectively (tabular form see Supplementary C4). The significance of the rho value verifies the necessity of considering residential selection bias. After controlling this bias, the results revealed that after controlling for possible selection bias in the primary model, park accessibility significantly influenced the PHQ9 score, and its effect size decreased with increased buffer size.

# 4.3.2. PSM

To avoid the observational differences between the freshmen and sophomores and above, we applied the PSM method to match two groups of students based on built environment features and socioeconomic and demographic characteristics. First, we calculated the propensity score based on logit regression. According to the propensity score, we used the kernel matching to match the freshmen and sophomores and above. Kernel matching was computed as follows Eq. (6):

$$\omega(\mu,\vartheta) = \frac{K(\frac{(p_{\mu}-p_{\vartheta})}{R})}{\sum K(\frac{(p_{\mu}-p_{\vartheta})}{R})}$$
(6)

where  $p_{\mu}$  and  $p_{\vartheta}$  refer to the propensity scores of the freshmen  $\mu$  and sophomores and above  $\vartheta$ ,  $\omega(\mu, \vartheta)$  is the weight used in kernel matching, and R is a bandwidth parameter.

Then, we did the weighted regression based on DID model. The results were presented in Fig. 6 (tabular form in Supplementary C5). It indicated that the impact of park accessibility on mental health is significant within 0.5 km and 1 km buffer sizes. The results were consistent with the benchmark results, which implied that after mitigating the systematic bias between freshmen and sophomores and above, park accessibility is still conducive to mental health.

### 4.3.3. Other robustness checks

To further check the robustness of conclusions, we regarded the freshmen as the preintervention group, and sophomores as the postintervention group. Then we estimated the impact of park accessibility on mental health in line with the benchmark analysis. The results were reported in Supplementary E, which indicates that park accessibility reduces the PHQ 9 scores of undergraduates within 0.5 km and 1 km buffer areas.

### 4.4. Possible mechanisms

Sections 4.2 and 4.4 have documented a significant and robust impact of park accessibility on mental health in 0.5 km and 1 km buffers. In this section, we tested several possible mechanisms, including cycling, and sleep qualities. We used the data of the cycling time per week to examine whether cycling is a pathway through which park accessibility affects mental health, and adopted the data of self-reported sleep quality (i.e., very bad, bad, general, good, very good) in the survey to quantify the sleep quality.

To determine the mental health improvement mechanism of park accessibility under the quasi-experimental framework, we followed the previous studies (Cao et al., 2022; Bianchi et al., 2022) and constructed the following model Eq. (7):



Fig. 5. Heckman two-step model: the effect of different buffers of park accessibility on mental health.



Fig. 6. PSM-DID: the impact of park accessibility on mental health within the 0.5 km, 1 km, 1.5 km, and 2 km buffers.

$$M_{\rm i} = \alpha_0 + \alpha_1 Accessibility_{id}$$

\* Exposure<sub>i</sub> +  $\alpha_2$ Exposure<sub>i</sub> +  $\alpha_3$ Accessibility<sub>id</sub> +  $\sum \tau_j * X_{ji} + \varepsilon_i$  (7)

where  $M_i$  represents the potential mediators (i.e., cycling and sleep quality). Accessibility<sub>id</sub> is a dummy variable: if the distance from the location of respondent *i* to the nearest park was within the radius buffer *d*, Accessibility<sub>id</sub> = 1; otherwise, Accessibility<sub>id</sub> = 0. The interaction term Accessibility<sub>id</sub> \* Exposure<sub>i</sub> is the variable of concern, which indicates whether the undergraduates *i* influenced by park accessibility.  $X_{ji}$  is the matrix vector of the control variables, and  $\varepsilon_i$  is the stochastic disturbance term.

Fig. 7 represented the estimation results of the critical variable. The estimation results for other variables were listed in Supplementary C6. The results demonstrated that park accessibility significantly increased

cycling within the 1 km buffer, which indicated that by promoting cycling, park accessibility promoted mental health in the 1 km buffer.

Fig. 8 represented the estimation results of the critical variable (for other variables see Supplementary C7). Park accessibility improves sleep quality within 0.5 km, 1 km, 1.5 km, and 2 km buffers, and its effect size decreased with increasing buffer sizes. The results indicated that park accessibility improved mental health through sleep quality.

### 5. Discussion

In this study, we collected quasi-panel data based on a large-scale cross-sectional dataset. We adopted a DID model to estimate the impact of park accessibility on mental health among undergraduates in China. In addition, we identify noticeable heterogeneity in the mental



Fig. 7. Park accessibility improves mental health by facilitating cycling.



Fig. 8. Park accessibility promotes mental health by improving sleep quality.

health effects of parks on various subgroups. There are three major findings.

First, with a quasi-experimental approach, we filled the gaps in existing studies and explored the robust relationship between park accessibility and mental health. Our results revealed that park accessibility leads to better mental health status within the 0.5 km and 1 km buffers after controlling for individual and neighbourhood factors. This is consistent with previous findings of significant associations between park accessibility and mental health (Akpinar, 2016; Orstad et al., 2020; Liu et al., 2017; He et al., 2022). Reducing mental stress (Ulrich et al., 1991; Ojala et al., 2019), stimulating physical activities (Akpinar, 2016; Orstad et al., 2020), and enhancing social cohesion (Kaźmierczak, 2013; Perez et al., 2015) are all plausible pathways underlying the link between park accessibility and mental health. The results remained robust when we accounted for selection bias.

Regarding the scale effect of the MAUP, the beneficial impacts of park accessibility on mental health were detected at the 0.5 km and 1 km buffer sizes but not at the 1.5 km and 2 km buffer sizes. The 1.5 km threshold may be beyond the normal walking distance (Millward et al., 2013); hence, frequent park use and associated park benefits may not be realized. Furthermore, the effect size of park accessibility decreased with increased buffer size. Generally, individuals prefer to visit green spaces close to where they live (Grilli et al., 2020). Furthermore, individuals' park usage declines with increased distance to the park, and parks being within 0.5 km have a greater impact on park use (Cohen et al., 2006; Wu et al., 2020). In this vein, individuals who are closer to a park are more likely to use the park and hence gain mental health benefits.

Second, access to parks had a positive effect on both male and female mental health within the 0.5 km and 1 km buffers, but it had a larger effect size on females than on men. One plausible reason is that females prefer to appreciate the aesthetic value of green spaces (Ode Sang et al., 2016). Krenichyn (2006) found that females are more likely to conduct physical activities in parks than males because the former tend to enjoy beautiful scenery and its therapeutic or spiritual qualities. Females are more likely to choose green travel routes than males, so females experience higher green exposure within average travel distance (Wu et al., 2022). Hence, females' preferences and attitudes towards parks may promote park use, which results in a larger effect size of park accessibility on females. However, at a 1.5 km buffer size, park accessibility affected only male mental health and had no significant impact on female mental health. Females are often concerned about security (Branas et al., 2011); thus, parks far away from residential locations trigger the sense of insecurity and hinder park use.

Third, park accessibility affected the mental health of both the highand low-living cost groups at the 0.5 km and 1 km buffer sizes. The effect size was larger in the high-living cost group. Regarding the 1.5 km buffer size, the impact of park accessibility on mental health was detected only in the high-living cost group. The disparity may be explained by the difference in the mobility and activity spaces of the two groups (Morency et al., 2011). People with low SES may restricted mobility due to limited resources or discrimination (Schwanen et al., 2015). They have fewer friends and fewer opportunities to participate in social activities (Perchoux et al., 2013). Thus, the active spaces of lowliving costs students are smaller than those of high-living costs students. In contrast, students with high-living costs tend to have more friends and more opportunities to go out, including using parks. Therefore, they receive more health benefits from the surrounding parks. In addition, Psaltopoulou et al. (2017) mentioned that people with high SES have healthier lifestyles than those with low SES. Students with high-living costs are more motivated to use parks. In this vein, students with high-living costs may be more likely to be influenced by nearby parks than students with low-living costs.

Overall, this study has several strengths. First, we captured the robust effect of park accessibility on the mental health of undergraduates. We transformed cross-sectional data to quasi-panel data by distinguishing pre- and post-intervention groups. Then, we adopted the DID method to examine causality, which overcame the limitation of traditional cross-sectional data and filled the gaps in this field (Frank et al., 2019; Hartig et al., 2014; Roberts et al., 2021). Second, we controlled for selection bias. We mitigated residential self-selection bias by selecting undergraduates who had little freedom to choose their residential locations. On the methodological front, we applied the Heckman two-step method and PSM method to mitigate two types of selection bias. Third, we examined the scale effect of the MAUP in the park accessibility-mental health context. We found that with increasing buffer sizes, the influence of park accessibility decreased. We further verified the moderating role of gender and high-living costs.

Nonetheless, several limitations of this study should be acknowledged. First, park accessibility was measured by distance to parks in this study, while perceived park accessibility can also influence park use (Park, 2017). Thus, perceived park accessibility, which is often measured by perceived travel distance or travel time, and the ease of getting to the park (Wang et al., 2015), should be considered in the future. Second, in addition to park accessibility, some studies also found that park features (Loukaitou-Sideris and Sideris, 2009; Cohen et al., 2006) and park quality (Zhang et al., 2013) affect park use. Future studies should explore how these factors affect the mental health benefits of parks. Third, this study only captured the built environment features of the campus and its surrounding areas but ignored the mobility difference of individuals. Future studies could collect individual travel data with portable devices, such as Global Positioning System. Fourth, it is challenging to clearly define the buffer area around university campuses that exert influence on the students. We defined it as a 500-m buffer of the campus centroid. There is a good reason to do so, because the average length of the longest radius from a campus centroid to its boundary is 527 m. However, it remains unclear whether all students reside near the centroids of their campuses. Future studies should accurately geocode the residential locations of the students when drawing different buffer sizes. Additionally, we simply discuss the park accessibility within a spatial buffers but did not discuss the confounding impact of socio-political boundaries on individuals. Future studies should pay more attention to socio-political boundaries.

### 6. Conclusion and recommendations

In this study, we discussed the robust link between park accessibility and mental health among Chinese undergraduate students by adopting a quasi-experimental research design. The results showed that park accessibility had a positive effect on mental health within the 0.5 km and 1 km buffers. With increasing buffer sizes, its impact decreased. Compared to male and low-living costs undergraduates, park accessibility had a greater impact on female and high-living costs undergraduates respectively. Therefore, policymakers and urban planners should establish more parks within a 1 km buffer surrounding campuses to improve the mental health of undergraduates.

### Funding

The research is supported by the Strategic Priority Research Program (A) of Chinese Academy of Sciences (Project No. XDA19040402).

### CRediT authorship contribution statement

Haoran Yang: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Funding acquisition. Jing Wen: Methodology, Formal analysis, Software, Writing – original draft. Yi Lu: Conceptualization, Writing – review & editing, Supervision. Qiuzhi Peng: Data curation, Software.

### **Declaration of Competing Interest**

The authors report no declarations of interest.

#### Acknowledgments

The data used in this research were derived from the China College Student Survey (Ethics No. 2018-L-25). We would like to thank Professor Li He at the first affiliated hospital of Kunming Medical University for providing the data. Furthermore, we contributed the data with support from Wenjie Du at East China Normal University.

### Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.127979.

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