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Pathways from street network design to symptoms of depression among emerging adults in China

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A R T I C L E I N F O

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A B S T R A C T

Streets comprise over 80% of all urban public space, while previous studies associated street network attributes with traffic and transport model choice, they did not examine network design in conjunction with symptoms of depression. This paper developed a path analysis model to examine the direct and indirect effects of street network designs on symptoms of depression among undergraduates. Road network density, road intersection density and public transit density were measured within 1 km buffers centered on university campuses. A survey that included the 9-item patient health questionnaire (PHQ9) addressed these effects and measured the incidence of symptoms of depression among a random sample of 22,060 Chinese undergraduates. After controlling for individual- and campus-level covariates, the results revealed that exposure to $PM_{2.5}$, poor sleep quality and unhealthy dietary pattern (excluding transport-related physical activity) mediated the relationship between specific street network attributes and symptoms of depression. Higher road density was found to alleviate symptoms of depression by increasing exposure to $PM_{2.5}$. Greater road connectivity tended to alleviate symptoms of depression by reducing exposure to $PM_{2.5}$ but to exacerbate symptoms of depression by worsening sleep quality and increasing the incidence of unhealthy dietary patterns. Better access to public transit inclined to ameliorate symptoms of depression by improving sleep quality but to exacerbate symptoms by increasing $PM_{2.5}$ exposure. These findings emphasize the need for strategies aimed at improving street network designs to include assessments of the aggregate effects on campus environs and the associated impacts on undergraduate mental health.

1. Introduction

By 2050, it is projected that over two-thirds of the global population will reside in cities (UN, 2019), and streets make up more than 80% of public spaces in modern cities comprises. While urbanization has brought about improvement in overall living conditions for urban residents, it also introduced new environmental and lifestyle risks. These risks include increased exposure to air pollution, ambient noise, unhealthy lifestyles such as physical inactivity, unhealthy dietary patterns and sleep disturbance, as well as an increased risk of mental disorders (Ventriglio et al., 2021). The prevalence of depression has been on the rise worldwide (Twenge et al., 2019), leading to a growing burden of disease globally (James et al., 2018; WHO, 2017). Furthermore, some countries have reported disproportionately high increases in the depression rate among younger adults (Steffen et al., 2020). This study examined the impact of street networks and associated mediating effects on the symptoms of depression among undergraduates who are important members of emerging adulthood cohort within the population (Arnett et al., 2014; Bishop et al., 2020).

Emerging adulthood, typically spanning from around age 18 to 29 years of age, is a distinct life stage characterized by identity exploration, instability, self-focus, and a feeling of being "in-between" adolescence

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and adulthood (Arnett et al., 2014; Swanson, 2016). This period offers individuals increasing personal freedom and opportunities. However, it is also a phase associated with a disproportionately high risk of mental health issues. As reported elsewhere, this population cohort has the highest incidence of depression of any age group (Klerman and Weissman, 1989; Malhi and Mann, 2018). Those who experience depression during this phase are at risk of facing challenges in achieving educational and career goals, as well as increased likelihood of encountering marital and parenting problems, sexual dysfunction, nicotine dependence, and substance abuse later in life, compared to their peers without depression (Kuwabara et al., 2007). The undergraduate years fall within the borderer period of emerging adulthood, and undergraduates are susceptible to the challenges and elevated risks of depression that this cohort faces (Akhtar et al., 2020). In China, more than 30% of undergraduates experienced symptoms of depression between 2009 and 2019 (Wang et al., 2020). With a population of 16.9 million undergraduates in 2018 (State Council of the People's Republic of China, 2022), the significant and ongoing occurrence of depression among Chinese undergraduates highlights the urgent need to address this mental disease burden and its impact on individuals' lives.

The built environment has increasingly been recognized as a root driver of a series of health issues in urban settings. It is believed to affect human health through two main paths: changes in exposure to environmental hazards (i.e., pollution and noise) and alterations in individual behaviors (Frank et al., 2019; Glazener et al., 2021; Liu et al., 2019b). Previous research has focused on network design as a means to develop sustainable communities by enhancing connectivity and density of road network, as measured by road intersection density and street network density (Hassen and Kaufman, 2016; Rychlewski, 2016). Such improved connectivity and density have been suggested to facilitate access to various destinations, encouraging the use of non-motorized transportation and public transit (Rychlewski, 2016; Zlatkovic et al., 2019). Public transit access, often measured by public transit density or distance to the nearest public transit (Sallis et al., 2016), is a critical element of sustainable transportation solutions, as it improves urban mobility and livability (Cullinane, 2003; Stiglic et al., 2018).

A growing body of research has consistently linked mental disorders, including depression, to individuals' behaviors and living conditions. These behaviors encompass choices related to physical activities (Ryu et al., 2022; Schuch et al., 2021), dietary patterns (Wang et al., 2018a; Weng et al., 2011), and sleep habits, which can impact sleep quality (Dinis and Braganca, 2018; Gregory et al., 2011). Moreover, the neighborhoods in which individuals reside and work influence their exposure to ambient particulate matter and levels of noise (Orban et al., 2016; Xue et al., 2021). These factors, to some extent, are influenced by surrounding street environment (Berrigan et al., 2010; Koohsari et al., 2014; Mahesh, 2021; Sallis et al., 2016).

Research have exhibited a positive association between street connectivity and individuals' engagement in walking and cycling for transportation purposes (Koohsari et al., 2014). These non-motorized modes of transport have been found to reduce symptoms of depression (Schuch et al., 2021) due to increased physical activities and decreased exposure to traffic-related pollutants and noise compared to motorized transport (Berrigan et al., 2010; Koohsari et al., 2014; Lundberg and Weber, 2014). However, neighborhoods surrounding with high intersection density, road network density and public transit availability tend to attract trips to retail outlets that offers snacks and fast food, potentially unhealthy diets associated with an increased risk of depression (Li et al., 2017; Weng et al., 2011). Additionally, intersections where vehicular stops and starts are frequent and commercial facilities are densely spaced have been observed to have higher concentrations of $PM_{2.5}$ (King and Clarke, 2015). To date, only a few studies have examined the association between street network design and mental illness such as depression (Yang et al., 2022; Zhang et al., 2019), and even fewer have explored the specific pathways through which street attributes influence depression.

Prior studies investigating the association between behavior/health and built environments have often been prone to residential self-selection, which can lead to spurious associations (Faber et al., 2021; Wu et al., 2021). To mitigate this bias, it is necessary to study populations where individuals' ability to choose residential locations based on their attitudes and preferences is minimized (Yang et al., 2021). Therefore, in this study, we focused on Chinese undergraduates who have little freedom to choose their residence, reducing the influence of residential self-selection. Furthermore, this population has been understudied in relation to the association between campus-centered neighborhoods and symptoms of depression (Yang et al., 2022).

To address knowledge gaps regarding the association between street network design and the mediating effects of depression, we conducted this study to examine the pathways between road intersection density, road network density and public transit density and symptoms of depression based on a nationwide sample of 22,060 Chinese undergraduates from 90 campuses. We tested two hypotheses: a) the densities of road intersection, road length and public transit surrounding campus environs are related to symptoms of depression among undergraduates; and b) there are mediating effects related to transport-related physical activity (TPA), unhealthy dietary pattern (UDP), sleep quality, and exposure to $PM_{2.5}$ on the associations between tested street network attributes and symptoms of depression.

2. Literature review

2.1. Street network design metrics

One commonly used metric to evaluate how well develop of a street network is street network density, which stands for the total length road of roads per specific unit area (Choi and Ewing, 2021). However, it is important to note that greater road density is not equal to better road connectivity (Marshall and Garrick, 2012), which refers the directness and availability of links from an origin to a destination (Koohsari et al., 2014; Zlatkovic et al., 2019). In some studies, street connectivity has been operationalized as the number of intersections per unit areas (Leonardi et al., 2017; Sallis et al., 2016; Yang et al., 2021). In addition to road density and connectivity aspects, public transit access has been a focus of prior research, as efficient public transport systems contribute to the livability and mobility of urban residents (Cullinane, 2003). Metrics such as density of public transit stations or distance to the nearest transit station have been used to measure access to public transit (Sallis et al., 2016). It has been noted that physical activity exhibits a negative association with public transit density but an insignificant association with distance to the nearest transit (Sallis et al., 2016). In this study, we used road network density, road intersection density, and public transit density to characterize the street network design surrounding campuses.

2.2. Potential pathways linking street network metrics to the symptoms of depression

Prior studies have proposed a framework combines behavioral and exposure-based pathways to explain the mechanisms linking the built environments to health outcomes (Frank et al., 2019; Glazener et al., 2021). In this section, we reviewed four potential pathways within this framework. These pathways are physical activity, dietary patterns, sleep quality, and exposure to $PM_{2.5}$.

TPA. Globally, walking and cycling for transportation contribute significant to total physical activity (Kruger et al., 2008). Engaging in these activities has been associated with a reduced risk of depression (Dishman et al., 2021). The choice of transport mode is strongly influenced by residential or working environs. Creating well-connected neighborhoods with high road density and intersections, mixed-land development promotes walkability, while neighborhoods with poor access to public transport and destinations tends to increase dependence on automobiles (Giles-Corti et al., 2016). Empirical studies have shown that higher street connectivity and road density are positively related to increased walking and cycling (Berrigan et al., 2010; Koohsari et al., 2014; Lundberg and Weber, 2014), potentially enhancing the positive effects on reducing depression (Dishman et al., 2021; Lee et al., 2012). Furthermore, some other research has indicated that connected neighborhoods tends to reduce origin–destination distances, thereby encouraging walking and cycling (Glazener et al., 2021; Koohsari et al., 2014; Qin et al., 2023). Likewise, higher densities of public transit options offer more transportation alternatives and may stimulate walking and cycling to transit stations (Qin et al., 2023; Sallis et al., 2016).

UDP. Despite earlier mixed findings (Chocano-Bedoya et al., 2013; Gougeon et al., 2015; Okubo et al., 2011), there is growing evidence suggesting that UDP is associated with an increased risk of depression (Oddy et al., 2018; Ruusunen et al., 2014). Specifically, an UDP characterized by high consumption of sweets, fatty foods and high-fat dairy has been implicated (Hemmati et al., 2021; Li et al., 2017). This type of diet may lead to alteration in endorphin levels, and elevated risk of cardiovascular diseases and brain atrophy, as well as increased levels of oxidative stress and inflammation (Lopez-Garcia et al., 2004; Marx et al., 2020; Westover and Marangell, 2002). In urban settings, convenience shops and fast-food establishments often cluster around intersections and public transit stops (Sharifi, 2019; Zlatkovic et al., 2019), which may contribute to residents in adjacent neighborhoods making suboptimal dietary choices (Bivoltsis et al., 2020; Poelman et al., 2018).

Poor sleep quality. Depression is frequently linked to difficulties in falling asleep at night and waking up in the morning (APA, 2013). In urban cities, road traffic noise has been associated with poor sleep quality (Frei et al., 2014; Pirrera et al., 2010) and decrease mental wellbeing (Giles-Corti et al., 2016). The density of road intersection contributes to increased noise levels due to more frequent stops and the need for additional braking and throttles (Arani et al., 2022). Congested intersections can also lead to excessive use of car horns by drivers. Public transit, particularly bus stops and railway stations, is another source of elevated noise level, and densely populated areas incline to have higher overall noise levels (Glazener et al., 2021; Sharifi, 2019).

Exposure to $PM_{2.5}$. Exposure to $PM_{2.5}$ has been identified as a potential risk factor for depression (Fan et al., 2020; Lim et al., 2012; Xue et al., 2021), making it a concern in urban environments. As proximate emission sources, higher densities of road networks, interactions and public transits are likely to contribute to increased ambient concentration $PM_{2.5}$ (King and Clarke, 2015; Lee, 2020; Wang et al., 2018b). At intersections, frequent stop-and-go traffic and vehicle acceleration form rest when traffic lights turn green are known to generate higher $PM_{2.5}$ emissions (King and Clarke, 2015; Wang et al., 2018b). Likewise, bus stop also with frequent the stop-and-go operations for passengers disembarking and boarding, that can result in elevated $PM_{2.5}$ concentration. For instance, Mahesh (2021) found that $PM_{2.5}$ concentrations at bus stops were 1.5 to 3.5 times higher than ambient air concentrations. Moreover, high connectivity and easy access to public transit can lead to transit-oriented development, which concentrates people and commercial establishments in urban areas and increases overall $PM_{2.5}$ concentrations (King and Clarke, 2015). On the other hand, a well-connected neighborhood with increased intersections and convenient access to public transit can encourage non-motorized transport modes over motorized ones (Sallis et al., 2016), thereby reducing $PM_{2.5}$ emissions (Aldrin and Haff, 2005; Lee, 2020; Sharifi, 2019; Zlatkovic et al., 2019).

2.3. Residential self-selection and its solutions

Residential self-selection is a confounding factor impact the association between the built environment and health outcomes (Faber et al., 2021; Wu et al., 2021). This type of bias often occurs when individuals' demographic, residential, and behavioral preferences influence both their choice of neighborhood and their behaviors (Faber et al., 2021; Yang et al., 2021). For instance, individuals with higher income and a preference for active travel are more likely to select a walkable and cyclable neighborhoods as their place of residence.

Three approaches have been proposed to address the data bias caused by residential self-selection. The first is to measure or control variables such as attitudes and preferences applied as covariates in environment-health studies (Humphreys et al., 1996; Wu et al., 2021). However, this approach is limited because of the difficulty in identifying and measuring variables capturing attitudes or preferences. The second is the use of quasi-experiments and longitudinal data approaches to research. These have advantages in exploring causalities in environment-health compared to cross-sectional data (McEachan et al., 2018; Xie et al., 2022). However, experimental/longitudinal data are more challenging to obtain due to ethical considerations, and studies that produce such data are often time-intensive and incur high monetary costs. The third approach, as in our case, is to sample participants with little freedom to choose their residence (Yang et al., 2021).

2.4. Undergraduates in Chinese context

The enrollment of Chinese undergraduate students has steadily increased over the past 20 years due to the implementation of a policy aimed at expanding colleges and universities admissions in 1999. In 2018, undergraduate students in China reached 16.94 million (State Council of the People's Republic of China, 2022). The management of campus housing and campus environment in China differs from the approaches taken by Western universities (Zhan et al., 2016). Unlike their counterparts, Chinese universities oversee the housing arrangements for all undergraduates and provide mandatory low-cost dormitories within the campus environs (He, 2015). This system limits undergraduates' freedom to choose their residential locations, effectively reducing the confounding effects of residential bias on the relationship between undergraduates' health and their living environments. Furth more, Chinese undergraduates typically engage in most of their daily routines (i.e., learning, eating, and living) within or around their campuses (Zhan et al., 2016). Consequently, Chinese undergraduate populations offer representative samples that are largely unaffected by the influence of residential self-selection bias, thereby increasing the suitability of these population for examining the relationships between individuals' environments and health.

3. Research design

3.1. Conceptual framework

Building upon previous research on pathways to health identified from the built environment (Frank et al., 2019) and to health from transportation (Glazener et al., 2021), we have developed a new conceptual framework that illustrates how the street network attributes, as examined in this study, may be associated with symptoms of depression (Fig. 1). It is believed that road density, road connectivity and access to public transit can alleviate symptoms of depression by promoting TPA and miatigating exposure to $PM_{2.5}$. Additionally, street connectivity also offers the potential to improve access to public transit (Zlatkovic et al., 2019). However, it is important to note that enhanced street connectivity and access to public transit may also have potential to exacerbate symptoms of depression by increasing unhealthy dietary intake or negatively affecting sleep quality.

3.2. Data

The data for this study were obtained from a nationwide cross-sectional survey on the determinants of health among undergraduates in China in 2018 (Ethical No: 2018-L-25). A multistage, stratified cluster sampling design was employed to recruit participants from 29 provincial units across the country. A total of 23,488 participants, aged from 16 to 29 years, were randomly selected from 90 campuses. Among them,

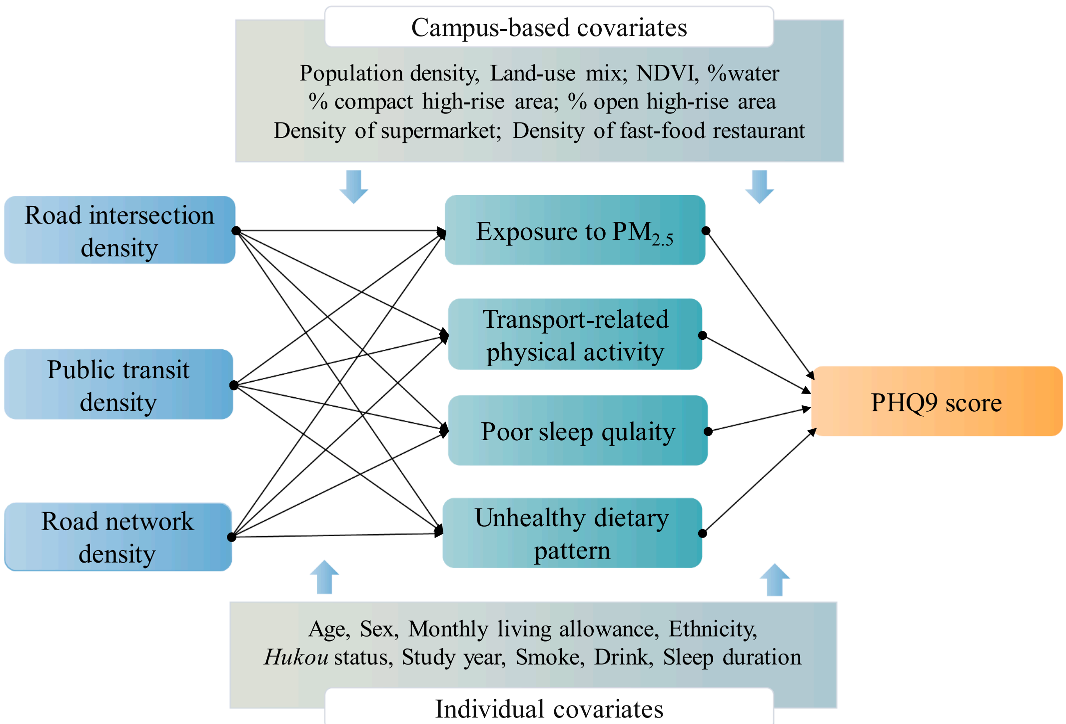

Fig. 1. Conceptual framework.

96.2% belonged to the emerging adulthood cohort. Each participant was interviewed in person by a fieldworker who collected information on potential symptoms of depression, lifestyles (i.e., travel behaviors, smoking and drinking habits, and sleep duration), demographics, and socioeconomic status (Table 1). A detailed description of the survey can be found elsewhere (Yang et al., 2021). Prior to participation, all individuals provided informed consent, and the study protocol was approved by the Ethics Committee. To accurately match the surveyed respondents with their corresponding campuses, the address of each surveyed campus was recorded and geocoded.

3.3. Variables

3.3.1. Symptoms of depression as outcome variable

Symptoms of depression were measured using the Chinese version of the 9-item patient health questionnaire (PHQ9), as detailed in Supplementary Table 1 (Kroenke et al., 2001). The Chinese version of PHQ9 has been shown to possess good reliability and validity (Wang et al., 2014). Each question in questionnaire captured the frequency of a specific negative mood state by the participants during the preceding two weeks (Gilbody et al., 2007; Kroenke et al., 2001). Responses were scored on a scale of 0 (not at all) to 3 (nearly every day) for each item. To derive a comprehensive measure reflecting the overall severity of depressive symptoms for each participant, the scores for individual questions were summed. The resulting PHQ9 total scores ranged from 0 to 27, with higher scores indicating greater level of symptoms severity.

3.3.2. Explanatory variables

Referring to prior studies (Liu et al., 2019a; Nordbø et al., 2018), we defined the campus surroundings using a concentric buffer with a standard 1 km radius centered on the centroid of each surveyed campus. Three variables were employed as explanatory measures: road network density, road intersection density, and public transit density. Road network density represents the total length of roads within the defined neighborhood (Choi and Ewing, 2021). Road intersection density, commonly used as an indicator of street connectivity, was calculated as the ratio of total amounts of road intersections with three or more ways per defined neighborhood (Ball et al., 2012; Koohsari et al., 2014; Sallis et al., 2016). Public transit density was determined as the ratio of the number of transits stops per defined neighborhood (Sallis et al., 2016). The data on the road intersections for three or more ways, road length and bus stops were obtained from Open Street Map for the year 2018 (Yang et al., 2021). Subsequently, we eliminated redundant road segments and connected fragmented road polylines to ensure data accuracy and completeness. To validate the data's quality and integrity, two experienced researchers conducted testing and verification against Gaode Map, the largest map supplier in China.

3.3.3. Candidate mediators

TPA. We assessed the level of TPA by using a weekly measure of time spent walking and cycling for transport among participants. The TPA indicator was derived from a questionnaire response, which captured travel frequency (*Fi*), origin–destination travel distance (*Di*), and average velocity (*Vi*) for walking and cycling. The questionnaire encompassed seven trip purposes associated with daily activities: learning, physical exercise, shopping, visiting friends, recreation, visiting the doctor, and working or performing an internship. Travel frequency (F_i) items were scored on a 6-point scale, ranging from "Never" or "Not Applicable" (encoded as 0 time/week), once in the past month (0.25 times/week), once every two weeks (0.50 times/week), two or three times a week (2.50 times/week), to (almost) daily (7.00 times/week). Responses for travel distance (D_i) were scored on a 5-point scale: <1.0 km (encoded as 0.5 km), 1.0 ~ 2.99 km (2.0 km), 3.0 ~ 4.99 km (4.0 km), 5.0 ~ 9.99 km (7.5 km), and ≥ 10 km (10.5 km). The answer to "What is the primary mode of transport you use to travel to each of the following activities per visit?" was scored on a 6-point scale: car, bus, subway, cycling, walking, and motorcycle. For participants who primarily used cycling or walking as their mode of transport, the TPA was calculated by summing the time spent on walking and bicycling (TPA $= \sum_{i=1}^{i=7} Fi \times (Di/Vi)$). According to (Stefansdottir et al., 2019), a velocity (*Vi*) of 5 km/h and 15 km/h was assigned for walking and cycling, respectively. To account for the skewed distribution, the TPA was values

Table 1
Descriptive statistics of the sample.

	N (%)	Mean (SD)	Median (IQR)	Range
Outcome variable:				
PHQ9 score [a]	–	5.08 (4.48)	4.00 (6.00)	0.00 – 27.00
Candidate mediators:				
TPA quantiles [a]	–	2.99 (1.41)	3(2)	1 – 5
UDP [a]	–	2.32 (0.88)	2.33 (1.33)	0.00 – 5.00
Sleep quality [a, c]	–	2.41 (0.88)	2.00 (1.00)	0.00 – 5.00
$PM^{b}_{2.5}$	–	40.3 (11.5)	37.7 (13.1)	17.0 – 68.9
Explanatory variables				
Road intersection density (10 intersections/km^2) [b]	–	18.3 (15.2)	13.8 (15.3)	0.96 – 81.5
Road network density (10 kms/km^2)	–	–	–	–
Public transit density (10 stations/km^2) [b]	–	5.73 (4.29)	5.25 (5.41)	0 – 23.57
Individual-level covariates:				
Age [a]	–	20.0 (1.74)	20.0 (2.00)	16.0 – 29.0
sex: Male (ref. Female) [a]	9,800 (44.4)	–	–	–
Monthly living allowance (ref. Low) [a, c]	–	2.52 (0.77)	3.00 (1.00)	1.00 – 5.00
Ethnicity: Minority (ref. Chinese-Han) [a]	2,985 (13.4)	–	–	–
Hukou status: Rural (ref. Urban) [a]	8,697 (39.4)	–	–	–
Study year: First year (ref. Others) [a]	5,908 (26.8)	–	–	–
Smoking: Yes (ref. No) [a]	1,696 (7.7)	–	–	–
Drinking: Yes (ref. No) [a]	8,672 (39.3)	–	–	–
Sleep duration (hours) [a]	–	7.44 (0.91)	7.50 (1.00)	3.00 – 12.00
Neighborhood-level covariates				
Lg (Population density) (population/ km^2) [b]	–	3.68 (0.62)	3.79 (1.02)	0.10–1.26
Land-use mix	–	0.43 (0.24)	0.49 (0.38)	0.00–0.81
NDVI	–	0.26 (0.09)	0.24 (0.10)	0.06–0.56
Coverage rate of water (%)	–	12.7 (9.39)	9.46 (8.58)	1.97–47.8
Coverage rate of compact high-rise area (%)	–	2.14 (6.03)	0.46 (1.40)	1.00–35.3
Coverage rate of open high-rise area (%)	–	13.8 (7.56)	13.3 (11.5)	1.11–34.2
Density of supermarket (10 supermarkets / km^2)	–	2.38 (2.36)	1.69 (3.11)	0.00–9.87
Density of fastfood restaurant (10 restaurants / km^2)	–	3.35 (3.01)	4.34 (3.11)	0.00–12.24

Abbreviations: TPA, transport-related physical activity; UDP, unhealthy dietary pattern; NDVI, normalized difference vegetation index; N, number; SD, standard deviation; IQR, interquartile range. [a] Descriptions for the individual variables based on 22,060 respondents comprising 96.2% of the emerging adults; [b] Descriptions for the neighborhood variables based on 90 campuses; [c] Sleep quality was measured on a scale from 1(excellent) to 5 (terrible).

were divided into five quantiles.

UDP. Following to Yin et al. (2023), the measurement of an unhealthy dietary pattern encompassed the totaling scores of fatty, diary, and sweetened food. The data for this measurement were collected through a questionnaire. Participants' response regarding their daily intake of each food category were evaluated using a 6-point scale: "Never" or "Not Applicable" (encoded as 0), very few (1), less (2), medium (3), more (4) to very many (5). By summing the individual item scores, the variable ranged from 0 to 15.

Sleep quality. Sleep quality was assessed using the single-item sleep quality scale. Participants' responses were scored on a 5-point scale, ranging from 1 (excellent) to 5 (terrible).

Particulate Matter ($PM_{2.5}$). The measurement for exposure to $PM_{2.5}$ was based on the annual average $PM_{2.5}$ concentration reported in 2018 by the nearest monitoring station to each target campus. The $PM_{2.5}$ data were obtained from the National Urban Air Quality Real-time Release Platform of China National Environmental Monitoring Center. On average, the distance between the monitoring stations and the target campuses was 4.6 km, with a standard deviation (SD) of 4.2 km.

3.3.4. Covariates

We incorporated various covariates at both individual and neighborhood level. At individual level, we controlled for demographic and behavioral attributes including age (in year), sex (male vs. female), ethnicity (minority vs. Chinese-*Han*), *Hukou* status (rural vs. urban), monthly living allowance grouped into five classes (from "< 500 yuan" to ">3000 yuan"), study year (1st vs. 2nd year and above), smoking (yes vs. no), drinking (yes vs. no), and sleep duration (in hours) based on prior research (Ibrahim et al., 2013; Yang et al., 2022).

Based on existing literature (Lee, 2020; Li et al. 2021; Liu et al., 2019b; Tu et al. 2019; Wu et al., 2022), we further controlled for population density, landscape distribution and spatial pattern, land-use mixture, as well as densities of supermarkets and fast-food restaurants. Population density was not only a proxy for urbanicity (Liu et al., 2019b), but an influencing factor for $PM_{2.5}$ exposure (Lee, 2020). Land-use diversity has been identified as an essential attribute of the built environment that influences dietary pattern and physical activity (Giles-Corti et al., 2016). The urban landscape, including vegetation and water bodies, as well as the spatial distribution pattern of cities such as build density, sky view factor are important factors in the generation, transport and settlement of $PM_{2.5}$ (Li et al., 2021; Tu et al., 2019), as well as in the formation of health-related behaviors (Dzhambov et al., 2019; Liu et al., 2019b; Yang et al., 2022). The accessibility of fast-food restaurants and supermarkets has been associated with unhealthy and healthy food choice and dietary intake (Atanasova et al., 2022; Roy et al., 2019). The population density data were obtained from Worldpop 2018 with a spatial resolution of 100 m and transformed logarithmically based on a scale of 10. Land-use mixture was assess using Shannon's entropy (Wu et al., 2022), using essential urban land use categories in China (Gong et al., 2020), which were openly downloaded from http://data.ess.tsinghua.edu.cn. The normalized difference vegetation index (NDVI), as a proxy for exposure to green space, were derived from cloud-free Sentinel-2 satellite images captured in September 2018, with a spatial resolution of 10 m × 10 m (Yang et al., 2021). The coverage percentage of water bodies (%), compact high-rise land (%), open high-rise land (%) were obtained from 2018 Local Climate Zones (LCZ) map (Stewart and Oke, 2012) provided by the Hong Kong University (Shi et al., 2019). The LCZ maps considered aggregately the elements including the height of roughness, terrain roughness, sky view factors, and aspect ratio (Jiang et al., 2023). Additionally, data on the number of supermarket and fast-food restaurant, which indicate food accessibility, were obtained from Gaode map in 2018 (https://lbs.amap.com/).

3.4. Statistical analysis

Descriptive analyses, including calculations of means, medians and proportions, were conducted to summarize the data. Pearson coefficients wwere used to assess correlations between the outcomes, candidate mediators, and the explanatory variables. Initially, linear mixed-effect models were applied to empty models for outcome variable and candidate mediators. The resulting intraclass correlation coefficients were found to be <0.06, indicating that traditional approach can do equal work since data did not violate the assumption of independence (Qiu, 2017). Consequently, multiple linear regressions adjusted for covariates were employed to examine the associations between street network design and the candidate mediators, followed by their association with PHQ9 scores.

In Model 1, adjustments were made for demographic and socioeconomic covariates, including age, sex, monthly living allowance, ethnicity, *Hukou* status, and study year. Model 2 further controlled for behavioral covariates, including smoking status, drinking behavior, and sleep duration. Additionally, in Model 3, adjustments were made for neighborhood-level covariates, including lg-transformed population density, land-use mixture, NDVI, coverage percentage of water, and the density of supermarkets and fast-food restaurants. The variance inflation factor values (VIFs) was calculated to assess the collinearity between independent variables. Model fits were assessed using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Following the evaluation, parallel mediation models linking street network design to the PHQ9 scores via the candidate mediators were tested using structural equation models (SEMs) based the on optimal Model 3 with the smallest AIC. The SEMs were estimated using MPLUS 8.0 and the maximum likelihood estimator, with 10,000 bootstrapped unstandardized coefficients and 95% confidence intervals (CIs) (Dzhambov et al., 2019; Roberts et al., 2021). The goodness of fit of the SEMs was evaluated using the comparative fit index (CFI), with values higher than 0.9, and the root mean square error of approximation (RMSEA), with values$<$0.05.

4. Results

4.1. Descriptive statistics

Descriptive statistics represents in Table 1. After excluding respondents with missing *Hukou* status before enrolling college (N = 1,428), a total of 22,060 respondents from 90 campuses met the survey parameters. Wilcoxon tests of the entire sample and the analytical sample, revealing no differences between them. The PHQ9 scores ranged from 0 to 27, with a median score of 4 (standard deviation [SD] = 4.48). The age of the respondents ranged from 16 to 29 years, with 44.4% being men, and the majority identified as Chinese-Han. In comparison to the age range, 96.2% of investigated undergraduates were belonged to emerging adulthood cohort.

The results of the correlation analysis are presented in Table 2. The PHQ9 scores exhibited a significantly positive correlation with UDP and sleep quality but a negative correlation with road intersection density and public transit density. Regarding the candidate mediators, intersection density showed a significantly positive correlation with UDP but a significantly negative correlation with exposure to $PM_{2.5}$ and TPA quantiles. Road network density and bus transit density displayed a significantly negative correlation with exposure to $PM_{2.5}$ and UDP but a significantly negative correlation with PA quantiles and poor sleep quality. Notably, road intersection density, road density and public transit density showed a significant and moderately positive correlation, suggesting a need for collinearity diagnosis before modelling. The resulting VIFs were $<$6 (see Supplementary Table 2), indicating the absence of multicollinearity (Yang et al., 2021).

4.2. Fitting performance of models

Table 3 presents the goodness of fit measures for the SEMs. Among the models tested, Model 3 demonstrated the best fit as indicated by the smallest AIC and BIC scores. The CFI value of 0.951 was deemed acceptable, while the RMSEA had a value of 0.044 (90 %CI: 0.041 – 0.047), indicating a nearly perfect fit for Model 3.

4.3. Associations between explanatory variables, candidate mediators and outcome

Fig. 2 and Supplementary Table 3 present the summarized results of SEM after adjusting for covariates at both individual and campus-level level. The analysis revealed that road intersection density was positively related to poor sleep quality, TPA quantiles and unhealthy dietary pattern but negatively associated with exposure to $PM_{2.5}$. Conversely, public transit density showed a positive association with exposure to $PM_{2.5}$ but a negative association with poor sleep quality. Road network density exhibited a negative association with poor sleep quality. PHQ9 scores were positively associated with exposure to $PM_{2.5}$, poor sleep quality and unhealthy dietary pattern, while a negative but insignificant association was observed in relation to TPA quartiles.

Supplementary Table 3 illustrated the results indicating that undergraduates studying in college surrounding higher NDVI, higher coverage percentage of water bodies and open high-rise land, and lower land-use mixture are likely to reported lower PHQ9 scores. Regarding individual covariates, females, ethnic minorities, and senior undergraduates were more likely to report higher PHQ9 scores.

Table 3
Results of the goodness of fit of the SEMs.

Measures	Model 1 [a]	Model 2[b]	Model 3[c]
Number of free parameters	49	65	105
Degree of freedom (df)	11	15	15
Comparative fit index (CFI)	0.915	0.921	<u>0.951</u>
Root mean square error of approximation (90 %CI)	0.040(0.037 – 0.044)	0.036(0.033 – 0.039)	0.044(0.041 – 0.047)
Akaike information criterion	511291.10	510292.21	<u>503086.52</u>
Bayesian information criterion	511683.18	510812.31	<u>503926.68</u>

Model 1 controlled for demographic and socioeconomic covariates including age, sex, monthly living allowance, *Hukou* status, ethnicity and study year;
Model 2 further controlled behavioral covariates including smoke status, drink behavior and sleep duration based on Model 1.
Model 3additionally controlled campus-based covariates including lg-transformed population density, land-use mixture, NDVI, coverage percentage of water, compact high-rise land and open high-rise land, as well as the density of supermarkets and fast-food restaurant based on model 2.

Table 2
Results of the bivariate correlation analyses.

Variables	PHQ9	TPA quantiles	UDP	Sleep quality	$PM_{2.5}$	Public transit density	Intersection density	Road network density
PHQ9 scores	1.000							
TPA quantiles	−0.007	1.000						
UDP	0.090**	−0.015*	1.000					
Sleep quality	0.294**	−0.003	0.026**	1.000				
$PM_{2.5}$	0.001	0.015	−0.024**	−0.048**	1.000			
Public transit density	−0.017*	−0.020**	0.070**	−0.019**	0.017**	1.000		
Intersection density	−0.022**	−0.021**	0.080***	−0.003	−0.044**	0.806**	1.000	
Road network density	−0.011	−0.033**	0.077**	−0.014*	0.066**	0.704**	0.825**	1.000

TPA, transported related physical activity spent weekly on walking and cycling; UDP, unhealthy diet pattern; $PM_{2.5}$, annual average concentration.
** $p < 0.01$ and * $p < 0.05$, that shows positive and negative correlation in red and blue text.

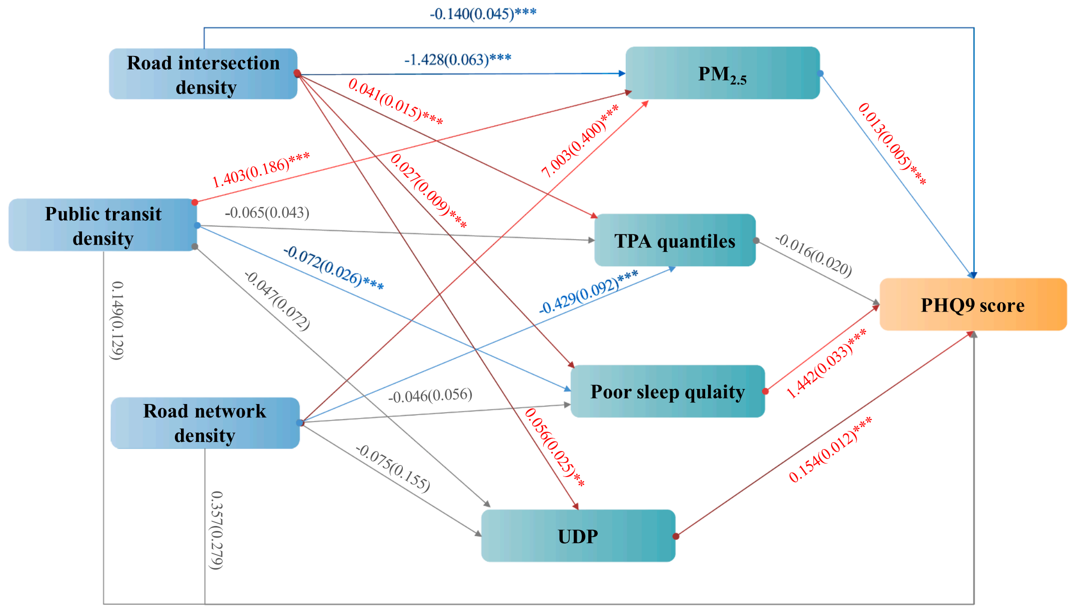

Fig. 2. Indirect and direct effects of street network design on PHQ9-based symptoms of depression. TPA, transported related physical activity spent weekly on walking and cycling; UDP, unhealthy diet pattern; $PM_{2.5}$, annual average concentration.The red lines denote significant and positive associations, the blue lines denote significant and negative associations, and the gray ones indicate insignificant associations. The data on line represents the estimated coefficient (standard error). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Furthermore, individuals from urban areas and those leading healthier lifestyles (i.e., non-smoking, non-drinking, and longer sleep duration) were more likely to report lower PHQ9 scores.

4.4. *Mediating effects*

The results of parallel path analysis (Table 4) revealed that both road intersection density and public transit density (except for road network density) had significant total indirect effects on the PHQ9 scores. Except for TPA quantiles, exposure to $PM_{2.5}$, poor sleep quality, and unhealthy dietary pattern were identified as significant mediators. The significant indirect effects indicated that increased road intersection density was likely to elevate PHQ9 scores by worsening sleep quality and promoting unhealthy dietary patterns, while it tended to potentially alleviate PHQ9 scores by mitigating exposure to $PM_{2.5}$. On the other hand, better access to public transit was likely to decrease PHQ9 scores via enhanced sleep quality but increase PHQ9 scores by increasing exposure to $PM_{2.5}$. Campuses surrounded by denser road networks were more likely to experience higher exposure to $PM_{2.5}$, resulting in a higher PHQ9-based depressive scores.

5. Discussion

5.1. *Main findings*

Our study investigated the associations between three measures of street network design (road intersection density, public transit density, and road network density), four candidate mediators (exposure to $PM_{2.5}$, TPA quantiles, unhealthy dietary patterns, and poor sleep quality), and symptoms of depression in a large nationwide sample of Chinese undergraduates. We found that road intersection density was directly and indirectly associated with symptoms of depression. On the other hand, both public transit density and road network only had indirect effect on symptoms of depression through increased exposure to $PM_{2.5}$. Interestedly, public transit density showed an inverse relationship with PHQ9 score, likely due to its positive impact on the improvement of sleep quality.

Consistent with previous studies (Baglioni et al., 2011; Dinis and Braganca, 2018), there was a positive association between poor sleep quality and symptoms of depression. Sleep quality acted as a mediator between symptoms of depression and road intersection and public

Table 4
The total, direct and indirect effects of street network design on symptoms of depression.

	Estimate (Stander error)	Estimate (95 %CI) from 10000-time bootstrap
Road intersection density:		
Total effect	−0.110 (0.038) ***	−0.110(-0.183 – −0.034)
Direct effect	−0.140(0.034) ***	−0.140(-0.210 – −0.072)
Total indirect effect	0.030(0.016) *	0.003(0.000 – 0.061)
→Exposure to $PM_{2.5}$	−0.018(0.006) ***	−0.018(-0.030 – −0.005)
→TPA quantiles	−0.001(0.001)	−0.001(-0.003 – 0.000)
→Poor sleep quality	0.040(0.014) ***	0.040(0.012 – 0.068)
→Unhealthy dietary pattern	0.009(0.004) ***	0.009(0.002 – 0.016)
Public transit density:		
Total effect	0.053(0.110)	0.053(-0.166 – 0.275)
Direct effect	0.149(0.102)	0.149(-0.051 – 0.355)
Total indirect effect	−0.096(0.043) **	−0.096(-0.183 – −0.015)
→Exposure to $PM_{2.5}$	0.013(0.005) ***	0.013(0.004 – 0.023)
→TPA quantiles	0.001(0.002)	0.001(-0.001 – 0.006)
→Poor sleep quality	−0.103(0.041) **	−0.103(-0.187 – −0.024)
→Unhealthy dietary pattern	−0.007(0.011)	−0.007(-0.026 – 0.011)
Road network density:		
Total effect	0.373(0.236)	0.373(-0.090 – 0.854)
Direct effect	0.357(0.217)	0.357(-0.071 – 0.802)
Total indirect effect	0.017(0.096)	0.017(-0.173 – 0.202)
→Exposure to $PM_{2.5}$	0.088(0.031) ***	0.088(0.027 – 0.146)
→TPA quantiles	0.007(0.007)	0.007(-0.005 – 0.023)
→Poor sleep quality	−0.066(0.089)	−0.066(-0.239 – 0.113)
→Unhealthy dietary pattern	−0.011(0.021)	−0.011(-0.051 – 0.031)

Abbreviations: TPA, transport-related physical activity; CI, confidence intervals.
All covariates at individual- and neighborhood- level were controlled for modeling.
Asterisks in red or blue, respectively, denote positive and negative associations.
Where *** denotes $p < 0.001$; ** $p < 0.01$; * $p < 0.1$.

transit density. However, road intersection and public transit density exhibited inverse associations with sleep quality, partially due to their different effects on exposure to traffic noise. Traffic, a primary source of noise that can disturb sleep (Frei et al., 2014; Orban et al., 2016; Pirrera et al., 2010; Quiñones-Bolaños et al., 2016), emanate from motor vehicles (Arani et al., 2022), particularly near intersections where stop-and-go traffic conditions often worsen the situation (Arani et al., 2022; Quiñones-Bolaños et al., 2016). By contrast, higher public transit density has the potential to improve sleep quality. Although increased bus stops may provide more opportunities for bus-related noise, most buses do not operate during the nighttime hours when undergraduates typically sleep. In China, the public transport system usually ceases operations at 22:00 h, while over 98% of undergraduates go to bed after that time (see Supplementary Fig. 1). On the other hand, higher public transit density has been positively associated with TPA (Qin et al., 2023; Sallis et al., 2016), which, in turn, is linked to better sleep quality (Lang et al., 2013).

Consistent with prior literature (Fan et al., 2020; Lim et al., 2012; Xue et al., 2021), there were significantly positive associations between exposure to $PM_{2.5}$ and depressive scores. We observed significant mediating effects of exposure to $PM_{2.5}$ on the associations between symptoms of depression and all three metrics of street network design. High densities of public transit and road network are likely to elevate PHQ scores through increased exposure to $PM_{2.5}$, suggesting a larger increase in $PM_{2.5}$ resulting from emission (King and Clarke, 2015; Lee, 2020; Wang et al., 2018b) compared to the reduction in $PM_{2.5}$ resulted from non-motorized transport instead of motorized ones (Aldrin and Haff, 2005; Lee, 2020; Sharifi, 2019; Zlatkovic et al., 2019). Most urban buses are equipped with heavy-duty, high-displacement engines, which generate large amounts of emissions per vehicle to accommodate all-day use (Pan et al., 2019; Song et al., 2015). Stop-and-go transit vehicle operations account for nearly half of the total emission of bus transport (Yu and Li, 2014), and higher $PM_{2.5}$ concentrations have been observed around bus stops (Arani et al., 2022; Mahesh, 2021). However, high road intersection density has the potential to alleviate symptoms of depression by mitigating exposure to $PM_{2.5}$, indicating a greater decrease in $PM_{2.5}$ emissions compared to an increase. Specifically, the decrease in $PM_{2.5}$ emissions resulted from increased use of active transport (Berrigan et al., 2010; Forsyth et al., 2008; Koohsari et al., 2014) is greater than the $PM_{2.5}$ emissions from stop-and-go traffic in intersections (Zlatkovic et al., 2019). Thus, our findings on how $PM_{2.5}$ acts as a mediator of symptoms of depression in the context of street connectivity and public transport support and advances previous scholarship.

The unhealthy dietary patterns showed only a mediating effect on the association between road intersection density and symptoms of depression. Our results support previous scholarly speculation that Western-style dietary patterns, characterizing by foods high in sugar, fats, and high-fat dairy products (as observed in the present study), may be associated with elevated levels of depression (Oddy et al., 2018; Ruusunen et al., 2014). We further speculated that this relationship may be influenced by well-connected neighborhoods with densely distributed intersections, which support a corresponding high density of retail establishments selling foods associated with western-style diets, particularly packaged convenience foods and fast food (Koohsari et al., 2014).

In contrast, we did not observe significant mediating effects of TPA quantiles on the associations between symptoms of depression and measured street network attributes. Consistent with existing literature (Forsyth et al., 2008; Koohsari et al., 2014; Lundberg and Weber, 2014; Zannat et al., 2020), high road intersection density was positively related to the time spent on active travel, which accounts for a significant portion of individuals' total daily physical activity. Unlike prior studies that reported negative associations between symptoms of depression and physical activity (Dishman et al., 2021; Schuch et al., 2021; White et al., 2017) and transport-related physical activity (Ryu et al., 2022), we found no association in this study, which aligns other scholarly findings (McKercher et al., 2009; Schuch et al., 2021; Teychenne et al., 2008). This lack of association may be partly attributed to the insufficient influence of TPA on the mood of undergraduates, as they primarily reside in dormitories and engage in most daily activities within or near college campus (He, 2015).

5.2. Strengths and limitations

This study had several strengths. We investigated a large, nationally representative sample across Chinese campuses. By employing SEMs, we not only examined the association between selected street network attributes and symptoms of depression but also explored the mediating effects of exposure to $PM_{2.5}$, sleep quality, and unhealthy dietary patterns, which have been rarely addressed in existing literature. Residential self-selection was implicitly addressed by focusing on undergraduate students because most Chinese undergraduates had little freedom to choose their place of residence.

Alongside these strengths, some limitations must be acknowledged. Firstly, similar to previous research (Koohsari et al., 2014; Sallis et al., 2016), our study design was cross-sectional, which precludes making causal inferences. More longitudinal evidence is required to understand the effect of street network design on mental health. Secondly, both the outcome and mediator variables were self-reported; introducing the possibility of recall bias (Mair et al., 2008). Thirdly, future studies should consider other unmeasured variables, such as additional topological network attributes and exposure to noise. Fourthly, although the surrounding street network design of the campus plays a crucial role in shaping depressive outcomes, some undergraduates may have resided outside the campus for various reasons, such as staying with their parents in the hometown or with their friends outside campus during the break times. Further research should also consider controlling for the exposure of break time on residential locations, especially in their hometowns, for undergraduate students.

6. Conclusions

Undergraduates' symptoms of depression were significantly associated with the densities of road intersection, road networks and public transits surrounding campus environments. With the exception of TPA quantiles, the other three candidate mediators showed significant mediating effects on the associations between symptoms of depression and the relevant street metrics. Specifically, higher road network density was likely to alleviate symptoms of depression by increasing exposure to $PM_{2.5}$. Greater road connectivity had the potential to ameliorate symptoms of depression by mitigating exposure to $PM_{2.5}$, while exacerbating symptoms of depression through worsening sleep quality and increased incidence of unhealthy dietary patterns. Better access to public transit tended to mitigate symptoms of depression by enhancing sleep quality but had an inverse effect by increasing $PM_{2.5}$ exposure. Multisectoral strategies could be implemented to address modifiable risk factors related to symptoms of depression among undergraduates at the neighborhood, campus and individual levels. Our findings suggest that when designing or updating campuses and their environments, urban designers and practitioners should holistically assess the multiple effects of different underlying pathways from the built environment and associated street networks to mental health. It is worth noting that both campus administrators and undergraduates can take steps to cultivate healthier lifestyles in campus environment by promoting healthy diets, addressing factors that hinder adequate sleep, and discouraging alcohol and tobacco use. Campus administrators should also prioritize the well-being of groups identified in this study as being at high risk of depression, particularly females and ethnic minorities, and those in higher academic years, as well as those from rural areas.

7. Ethnic approval

First Affiliated of Kunming Medical University: 2018-L-25.

CRediT authorship contribution statement

Xiangfen Cui: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Jing Wen:** Methodology, Formal analysis. **Haoran Yang:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Marco Helbich:** Writing – review & editing. **Martin Dijstg:** Writing – review & editing. **Hannah Roberts:** Writing – review & editing. **Senlin Tian:** Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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