

## Research Article

# From a visual standpoint: Exploring the influence of the built environment, especially road ratio, on mental wellbeing before and after the COVID-19 outbreak in Hong Kong<sup>☆</sup>

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## ARTICLE INFO

**Keywords:**  
Built environment  
Mental health  
Machine learning  
Road ratio  
COVID-19

## ABSTRACT

Road ratio, representing the proportion of roads in the street view, exerts varying degrees of visual influence on the mental well-being of residents. In our study, we surveyed the psychological conditions of 2,636 Hong Kong residents across four periods: before, during, and after the pandemic. Utilizing machine learning algorithms, we analyzed street view images within a 100-m radius of the residents' locations to determine the proportion of roads within the street views. This served as a representation of the visual impact of roads on residents. Subsequently, we employed Ordinary Least Squares (OLS) models and Multinomial Logit (MNL) models to investigate the relationship between the proportion of road presence in street views and the frequency of various forms of stress among residents across the four identified periods. Our findings indicate that an increase in road ratio correlates with a higher incidence of diverse stress forms. This effect was particularly pronounced during the pandemic, where the influence of road ratio on the frequency of depressive episodes intensified and persisted even after the pandemic had ended. The significance of our research lies in its implications for future urban planning, specifically in how road ratio near residential areas can be reduced and offset with more natural elements to mitigate the adverse effects of road ratio on residents' mental health.

## 1. Introduction

Mental wellbeing problems frequently manifest and can lead to significant impairment across numerous countries worldwide (Kessler et al., 2009; Vigo, Thornicroft, & Atun, 2016). One out of every four individuals in the world will encounter a mental wellbeing issue at some point during their lifetime (Queensland brain institute, 2023). To make matters worse, 70% of individuals with mental wellbeing issues do not seek treatment from a psychiatrist (Henderson et al., 2013). This highlights the fact that mental wellbeing challenges have emerged as a widespread concern in public health globally. Mental wellbeing issues have long been recognized as a mainstream public health concern in Hong Kong (Food and Health Bureau, 2017). Currently, 60% of Hong Kong's adult population is in

<sup>☆</sup> This work was supported by the Hong Kong Research Grants Council (RGC) Research Fellow Scheme (RFS) [grant number HKUST RFS2425-6H03]; the Public Policy Research (PPR) Funding Scheme of the Chief Executive's Policy Unit [grant number 2024.A7.032.24B]; the Inaugural CLP Research Fellowship Programme Award [grant number RFP2022HKUST]; the Innovation and Technology Support Programme, Hong Kong SAR Government [grant number ITS/003/24SC]; and the RGC Strategic Topics Grant (STG) [grant number STG2/E- 605/23-N].

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<https://doi.org/10.1016/j.jum.2024.09.004>

Received 3 June 2024; Received in revised form 31 July 2024; Accepted 10 September 2024

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a state of suboptimal psychological health (Mindhk, 2019), and approximately one out of every seven individuals in Hong Kong are projected to encounter a common mental wellbeing problem at some point (Food and Health Bureau, 2017). The COVID-19 outbreak has further exacerbated mental wellbeing issues among residents, doubling symptoms of depression and overall unhappiness, with older individuals experiencing notably higher increases in stress levels (Zhao et al., 2020; Zhu & Tan, 2021). This situation underscores the grave reality of mental wellbeing problems in Hong Kong and highlights the need to understand the factors that influence mental wellbeing. Research indicates that mental wellbeing is affected by both intrinsic and extrinsic factors, with the built environment playing a vital role as an external influence (Alexander Arguello et al., 2019; Choi, 2022; Ochodo et al., 2014; Taniguchi et al., 2022). This environment includes elements such as green spaces, architectural structures, pedestrian infrastructure, vehicular presence, natural elements, signage, and pollution, all of which contribute significantly to the exacerbation or alleviation of mental wellbeing issues (Beemer et al., 2021; Hoisington et al., 2019; Moore et al., 2018; Sullivan & Chang, 2011, pp. 106–116; Weich et al., 2002), particularly in the densely populated urban milieu of Hong Kong (see Table 3, 4 and 5).

In our study, we conduct a comprehensive literature review to systematically examine the built environment factors influencing mental wellbeing. On this basis, we employed a questionnaire survey to assess the changes in Hong Kong residents' mental well-being before and after the pandemic. Additionally, we utilized street view images to visually analyze the proportions of various objects within the street-view images, aiming to determine the psychological impact of different street-view components. Hong Kong's dense urban design, with roads closely packed around living spaces (Task Force on Land Supply, 2018), may affect the mental wellbeing of its residents who are constantly exposed to this environment. At present, there is a notable lack of targeted research in Hong Kong aimed at examining how these road networks, from a visual standpoint, influence residents' mental wellbeing. So, it is essential to investigate this potential psychological impact and consider enhancements to the urban layout to promote well-being.

This article contributes to the existing literature in three aspects. First, understanding the impact of road ratio on residents' mental wellbeing from a visual perspective reveals significant insights. Second, our study has been found that during the pandemic, the density of roads exacerbated the mental strain on residents, with mental wellbeing issues lingering even after the pandemic. Third, proactive suggestions for future urban road constructions are proposed to alleviate the mental wellbeing concerns of the populace, highlighting the urgent need for urban planning that takes into consideration the psychological well-being of its residents.

The rest of the article is arranged as follows. Section 2 introduces the Literature Review. Section 3 describes the process of collecting street view data and residents' mental wellbeing data. Section 4 introduces method of processing street View image data and selecting econometric models. Section 5 shows the results of the relationship between the road ratio and residents' mental wellbeing. Section 6 gives the discussion about the results. Section 7 draws the final conclusions.

## 2. Literature review

The built environment can be considered as the man-made settings that accommodate human activities, encompassing a variety of scales from individual buildings and green spaces or parks to larger entities like neighborhoods and cities, often inclusive of their associated infrastructure (Coleman, 2017; Zhu et al., 2023). Current studies have shown that the built environment have substantial effects on mental wellbeing. Many urban elements such as blue and green open space, crosswalks, vehicles, pedestrians, natural elements, signs, and pollution in the street can have direct or indirect effects on residents' psychological status (Van Kamp & Davies, 2008; Helbich et al., 2019; Hematian & Ranjbar, 2022; Yue et al., 2022). To better find the impacts of the urban built environment on mental wellbeing, we have summarized these factors into five main categories, as follows.

### 2.1. Natural environment

The combination of elements like the sky, green space, and trees can represent the natural environment Wang et al. (2022). Under normal circumstances the sky is always blue in the daytime, and current research finds that sky blue has a strong relationship with residents' psychology, it will cause people to release special hormones which can calm residents down (O'connor, 2011). In addition, the degree of the visibility of the sky can also represent openness to make street more attractive, and finally make residents feel more comfortable (Tang & Long, 2019). Meanwhile, Green space in the street view can include parks, lawns, trees and greenbelt. According to current studies, greenness has positives influences on residents' psychology, even if people give a short time visit to green space, greenness can still play a role in relieving stress and feeling content (Laforteza et al., 2009; Tyrväinen et al., 2014; Wang et al., 2019).

### 2.2. Traffic flow

Traffic flow can be concerned with vehicle and pedestrian flow in the street view (Dai et al., 2021). Residents may be fear of gathering of the vehicles and pedestrians on the street, and excessive vehicles and pedestrians may cause serious anxiety on the residents (Cherney, 2020). And the research here is mostly considering the impact of road vehicles on people's mental wellbeing, without considering the potential impact of road network density.

### 2.3. Obstruction

Tall buildings will block the horizontal eye view of residents and make the environment more enclosed. Today's cities are relatively enclosed environmental space built by high-rise building especially in Hong Kong. Therefore, we can consider buildings as obstacles that

obstruct the line of sight. For residents who have been exposed to this type of built environment for a quite long time, they are more likely to become more anxious and cause psychological problems at last (Hao et al., 2022).

#### 2.4. Complexity

With the development of the urban cities, many supporting infrastructure objects are assembled in every corner of the cities including signs, wires and lamp poles. These pieces of street furniture are vital elements of the built environment, simultaneously adding complexity to street scenes (Ewing & Handy, 2009). The presence of signage on the streets can convey a wealth of commercial and non-commercial information, but an excessive amount of such information clutters the visual space and can create a sense of confusion (Ramadan et al., 2023). Meanwhile, the complexity of a scene is significantly enriched by the presence and movements of individuals. This holds true not solely due to the discrete presence of people as static objects, but also owing to their perpetual motion (Ewing & Handy, 2009). This type of complexity is closely correlated with residents' psychology because it may cause the surrounding residents feel stressed, hopeless and overwhelmed (Sherrie bourg, 2012).

#### 2.5. Road ratio

Road ratio here refers to the proportion of roads depicted in streetscape images. The road in our study is composed of various types of road surfaces including highway, motor vehicle lanes, and non-motorized vehicle lanes. Currently, we know that a well-designed road network contributes to increased accessibility (Mohammad et al., 2021; Zhu et al., 2022; Zhu & Guo, 2022). The good accessibility can facilitate the communities more livable and improve the efficiency of commuting, these ultimately improved outcomes are strongly correlated with residents' psychology (Ewing & Handy, 2009). However, it may simultaneously lead to an overly dense network of roads. An excessively dense environment can overstimulate the senses, creating feelings of overcrowding that could ultimately influence people's mental wellbeing (Wen et al., 2020). Meanwhile, the steep land costs in Hong Kong have led to the development of a comparatively compact network of roadways (Task Force on Land Supply, 2018). Therefore, it would be reasonable to infer that Hong Kong's overly concentrated network of roads could impact residents' mental wellbeing. Currently, there is discussion on the negative impact of noise and air pollution from vehicles on the mental wellbeing of nearby residents (Clark et al., 2020). But there is almost no research exploring the psychological impact on residents from an overly dense road network from a visual perspective, especially in Hong Kong. Therefore, through our research, we can understand whether the road network has more positive or negative effects on the mental wellbeing.

Moreover, such kinds of built environment could potentially amplify the mental wellbeing repercussions for inhabitants amid the COVID-19 crisis. Many studies indicate that restricted movement spaces can significantly impact the level of psychological well-being (Bastastini, Miller, Horton, & Morgan, 2023; Kapoor & Trestman, 2016, pp. 199–232). Therefore, the pandemic's restriction on activity options means residents spend more time in their immediate surroundings, potentially leading to greater negative psychological shifts. Existing studies reveal that the COVID-19 pandemic precipitated severe psychological problems, especially among frontline workers, individuals residing in areas with low housing quality and high population density, and those with pre-existing mental wellbeing conditions (Amerio et al., 2020; Asim et al., 2021; Moreno et al., 2020). The frequency of mental wellbeing issues has increased compared to the period before the COVID-19 pandemic outbreak (Choi et al., 2020). However, there is a notable lack of research concerning which types of urban built environments exacerbate psychological issues during COVID-19 pandemic and which are conducive to mental wellbeing recovery following such a health crisis.

### 3. Data collection and statistics

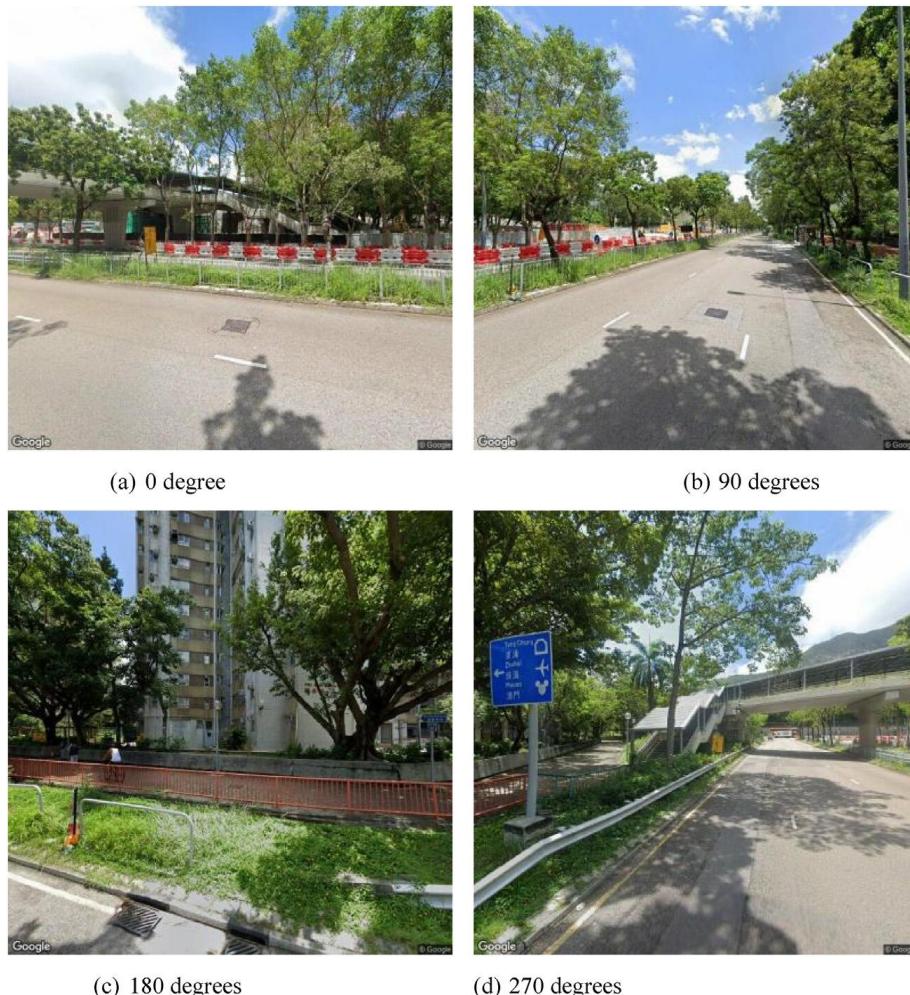
The Center for Applied Economic Social and Environmental Research at the Hong Kong University of Science and Technology executed four comprehensive surveys aimed at capturing behavioral changes among Hong Kong residents before and after the pandemic. These surveys, which involved a random sampling of approximately 3,000 residents, gathered detailed data on variables such as employment status, income levels, consumer habits, housing conditions, and psychological well-being, all of which hold significant relevance to the ongoing research. We typically receive around 2600 valid responses each time and use the same questionnaire for all participants in different periods. The inaugural survey was carried out in the latter half of 2019, predating the COVID-19 pandemic; The second set of statistical data pertains to the first wave of the pandemic, spanning from February to April 2020; The third data collection period corresponds to Hong Kong's most severe and final fifth wave of the pandemic, from February to April 2022. Whereas the final survey phase commenced in May 2022, the government further relaxed social distancing measures, which represents the gradual conclusion of the fifth wave of the pandemic in Hong Kong. It was during this time that we conducted the final round of surveys to understand the psychological changes among residents during the post-pandemic period. This sequential approach facilitates a nuanced analysis of the shifts in residents' behaviors and mental wellbeing in the post-pandemic context. In our questionnaire for assessing psychological dimensions, we utilized six carefully chosen questions to represent six types of stress from the Depression, Anxiety, and Stress Scale - 21 Items (DASS-21). This self-report scale is meticulously crafted to gauge the negative emotional states of depression, anxiety, and stress (Lovibond & Lovibond, 1995).

And the research incorporates street view imagery as a pivotal data source. Utilizing Google Maps' technology, we can gain access to

comprehensive, 360-degree panoramic views of Hong Kong's streetscape. This visual data, derived from the surveyed participants' residential locations, enables the extraction of street view images covering a 100-m radius around these locales, thereby capturing essential attributes of the urban built environment. Images captured from four cardinal directions—0, 90, 180, and 270°—contribute to assembling a holistic, 360-degree panoramic vista of the area, enriching the study's data reservoir. By applying the relevant algorithms, we can determine the proportional size that each object occupies within the entire image.

This table provides descriptive statistics for the variables used in the study on the influence of the built environment, especially road ratio, on mental health and well-being before and after the COVID-19 outbreak in Hong Kong. This section includes various measures of the built environment (in Panel A), including road ratio, sidewalk coverage, building coverage, presence of walls, fences, poles, traffic lights, traffic signs, vegetation, terrain, sky, and the presence of people, riders, cars, trucks, buses, trains, motorcycles, and bicycles. The statistics show the mean, standard deviation, minimum, and maximum values for each of these built environment variables. Our article suggests that in Hong Kong, the road (24.2%) and traffic light (14.8%) account most proportion in our built environment, followed by vegetation (10%) and building (3.7%). Conversely, Fens (0.03%) and Sky (0.03%) account for the least proportion. In Panel B, the table also provides descriptive statistics for the individual-level control variables gathered through surveys. These include factors such as: Gender, Year of birth, Education, Marital, Income individual, Income and Receive support.

Panel C provides statistics for Mental Wellbeing. This section includes measures of mental wellbeing, specifically various stress indicators (stress01 to stress06) measured at four different phases (Phase 1 to Phase 4). The stress indicators range from 0 to 3, with higher values indicating higher levels of stress. Generally, before the COVID-19 pandemic, the stress level remained at a comparatively low level. The values for stress01-06 were 0.81, 0.50, 0.39, 0.17, 0.61, and 0.48, respectively. However, there was a steep increase in stress levels at the beginning of the COVID-19 pandemic, which is termed as Phase 2. During this phase, the values for stress01-06 increased to 1.12, 0.71, 0.83, 0.28, 0.89, and 0.74. In Phase 3, when the COVID-19 pandemic aggravated, the stress level continued to increase further. The values for stress01-06 rose to 1.25, 0.82, 0.90, 0.35, 0.97, and 0.80. During the post-COVID period (Phase 4), the stress level almost returned to the levels observed in Phase 2. The values for stress01-06 were 1.12, 0.74, 0.66, 0.31, 0.84, and 0.67, respectively.



**Fig. 1.** 360-degree panoramic street view images.

Source: Google Street View images

## 4. Method

### 4.1. Machine learning

To gain a visual perspective on the built environment, we employ the advanced deep learning framework DeepLabv3+, and successfully segmented and isolated every element from the street-level photographs (Cordts et al., 2016). DeepLabv3+ is an advanced deep learning-based image semantic segmentation method that enables pixel-level segmentation of objects. The framework is the latest iteration of the Deeplab neural network series developed by Google, representing a significant advancement in its third generation. It can recognize and differentiate different objects in an image. This model performs exceptionally well in urban landscapes, pedestrian detection, and other scenarios, accurately delineating the image (Gou et al., 2022). This cutting-edge algorithm enabled us to use the corresponding color to represent each part and precisely quantify the presence of diverse features like trees, grasslands, skies, pedestrians, and cars within the imagery (Fig. 1). This model underwent training using the cityscapes dataset and attained an accuracy rate of 86.5%, demonstrating proficiency in segmenting 19 distinct object categories (Chen et al., 2018). Based on these proportions, we used the formulas outlined in Table 1 to determine the proportion of each key element in the built environment (see Table 2) (see Fig. 2).

### 4.2. Econometric model

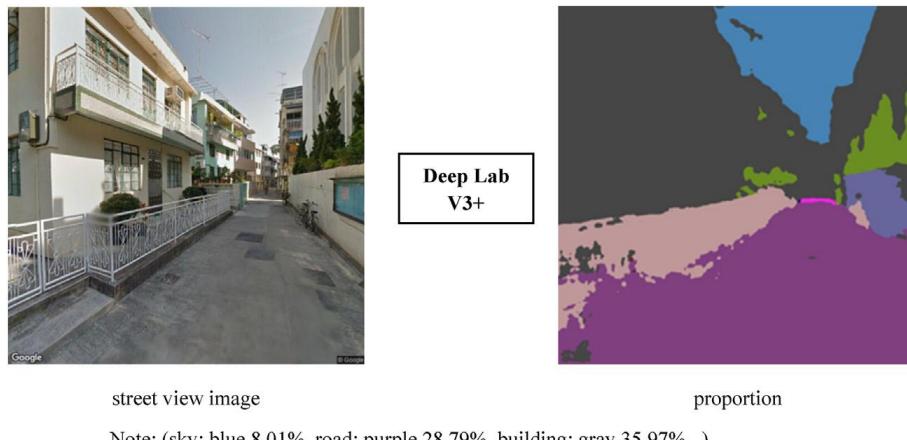
#### 4.2.1. OLS

$$y_i = RR_i + SW_i + X_i + \theta_i + \varepsilon_i \quad (1)$$

In our article, where the focus is on the stress level of individual  $i$ , we employ six different stress measures: stress 01 (frequency of failing getting enthusiastic), stress 02 (frequency of feeling meaningless of life), stress 03 (frequency of feeling panic), stress 04 (frequency of having breathing difficulty), stress 05 (frequency of having difficulty to relax), and stress 06 (frequency of overreacting). In terms of measuring frequency, 0 represents rarely/Never, 1 represents occasionally (1–2 days), 2 represents sometimes (3–4 days), and 3 represents always/usually (5+ days). Road ratio (RR) for individual  $i$  is quantified as the ratio of road area within a 100 m radius, as observed in one picture. The perceived sidewalk quality (SD) is also included in our analysis. We incorporate a set of control variables ( $X$ ), including individual income, household income, gender, education level, year of birth, marital status and support from government scheme to account for potential confounders. Individual fixed effects are denoted by  $\theta_i$ , and error terms are represented by  $\varepsilon_i$ . Standard errors are clustered at the district level to account for within-group correlations.

#### 4.2.2. Multinomial logit model (MNL)

This study examines the relationship between building environments and the severity of psychological disorders. We categorize disorder severity into four distinct outcome levels, treating this as our dependent variable. Our independent variables encompass aspects of the built environment hypothesized to influence psychological well-being, assuming these environmental factors are not dependent on other variables. To analyze these relationships, we employ a Multinomial Logit Model (MNL), which clarifies the association between each building environment variable and the potential outcomes of psychological disorder severity. The MNL requires selecting a reference outcome category against which the others are compared. We designate Level 1 – representing individuals who have never experienced mental wellbeing issues – as our reference group. This choice stems from Level 0 representing the mildest outcome on the spectrum of mental wellbeing severity. Therefore, considering a resident ‘ $n$ ’ experiencing psychological disorder severity level ‘ $j$ ’, the propensity function for this outcome is:



**Fig. 2.** Analyzing the proportion of street view images via using Deep Lab V3+ algorithm.

Note: (sky: blue 8.01%, road: purple 28.79%, building: gray 35.97% ...). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**

Descriptive Statistics of all independent and control variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Build Environment					
Road	3063	0.2420461	0.1239688	0	0.5982
Sidewalk	3063	0.0234024	0.0593286	0	0.6479
Building	3063	0.0365454	0.0190144	0	0.3161
Wall	3063	0.0049345	0.0091807	0	0.1071
Fence	3063	0.0002838	0.0009306	0	0.0332
Pole	3063	0.0010544	0.0007067	0	0.0063
Traffic light	3063	0.1479624	0.0841846	0	0.4205
Traffic sign	3063	0.0164325	0.0382853	0	0.3061
Vegetation	3063	0.1003139	0.0545702	0	0.3176
Terrain	3063	0.0084463	0.0277042	0	0.1824
Sky	3063	0.0002652	0.0019421	0	0.0984
Person	3063	0.017561	0.0116226	0	0.1098
Rider	3063	0.0033825	0.0053838	0	0.0474
Car	3063	0.0013918	0.0021819	0	0.0274
Truck	3063	0.0055466	0.0049216	0	0.0369
Bus	3063	0.0003777	0.0018994	0	0.0203
Train	3063	0.0005379	0.0005003	0	0.0041
Bicycle	3063	0.037252	0.0748668	0	0.3593
Panel B: Individual Characteristics					
Gender	3016	1.531167	0.4991104	1	2
Year of birth	3016	1978.97	14.0791	1930	2003
Education	3016	4.047414	1.323874	1	6
Marital	3005	1.670882	0.5989066	1	3
Income individual	2858	2.948915	1.715965	1	7
Income	2858	4.015745	1.856441	1	7
Receive support	2850	0.0691228	0.2537074	0	1
Panel C: Mental Wellbeing					
stress01 (Phase 1)	2636	0.806525	0.8245125	0	3
stress02 (Phase 1)	2634	0.5030372	0.7955621	0	3
stress03 (Phase 1)	2633	0.385112	0.7004928	0	3
stress04 (Phase 1)	2631	0.1702775	0.4846369	0	3
stress05 (Phase 1)	2631	0.609274	0.8342328	0	3
stress06 (Phase 1)	2630	0.4756654	0.7395635	0	3
stress01 (Phase 2)	2636	1.122914	0.9108613	0	3
stress02 (Phase 2)	2634	0.7164009	0.9147381	0	3
stress03 (Phase 2)	2633	0.8378276	0.9298643	0	3
stress04 (Phase 2)	2631	0.2831623	0.6116872	0	3
stress05 (Phase 2)	2631	0.8981376	0.9466171	0	3
stress06 (Phase 2)	2630	0.7494297	0.877831	0	3
stress01 (Phase 3)	2636	1.250759	0.9789528	0	3
stress02 (Phase 3)	2634	0.8211845	0.9815576	0	3
stress03 (Phase 3)	2633	0.9046715	0.966591	0	3
stress04 (Phase 3)	2631	0.3527176	0.6801582	0	3
stress05 (Phase 3)	2631	0.9794755	0.9767043	0	3
stress06 (Phase 3)	2630	0.8015209	0.8908465	0	3
stress01 (Phase 4)	2636	1.121017	0.9576211	0	3
stress02 (Phase 4)	2634	0.745634	0.9582185	0	3
stress03 (Phase 4)	2633	0.6650209	0.8678985	0	3
stress04 (Phase 4)	2631	0.3128088	0.6506967	0	3
stress05 (Phase 4)	2631	0.8445458	0.9317834	0	3
stress06 (Phase 4)	2630	0.6768061	0.8350639	0	3

Note: In Panel A, Build Environment represents the proportion of each factor in the figure. These factors include Road, Sidewalk, Building, Wall, Fence, Pole, Traffic light, Traffic sign, Vegetation, Terrain, Sky, Person, Rider, Car, Truck, Bus, Train and Bicycle. In Panel C, stress 01 (frequency of failing getting enthusiastic), stress 02 (frequency of feeling meaningless of life), stress 03 (frequency of feeling panic), stress 04 (frequency of having breathing difficulty), stress 05 (frequency of having difficulty to relax), and stress 06 (frequency of overreacting). Phase 1 was carried out in the latter half of 2019, predating the COVID-19 pandemic; Phase 3 spanned from February to April 2020; Phase 3 was conducted from February to April 2022. Whereas the final survey phase (phase 4) commenced in May 2022.

$$y_{nj} = \beta_1 RR_{nj} + \beta_2 SW_{nj} + \beta_3 X_{nj} + \epsilon_i \quad (2)$$

Where  $Y_{nj}$  is a function of covariates that determines the severity,  $\beta$  is a vector of estimable coefficients for severity level of  $j$ . Particularly,  $\beta_1$  is for road ratio while  $\beta_2$  is for sidewalks.  $X_{nj}$  is a vector of covariates and  $\epsilon_{nj}$  is a random error term that accounts for unobserved factors influencing psychological disorders severity level. The errors are assumed to be independently and identically distributed with

**Table 2**

Estimation of the OLS for six types of stress in the latter half of 2019 in Hong Kong.

Time = 01	(1) stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Road Ratio	0.59 <sup>a</sup> (0.22)	0.35 <sup>c</sup> (0.093)	0.19 (0.298)	0.16 (0.243)	-0.012 (0.956)	0.35 <sup>c</sup> (0.087)
Sidewalk	-0.37 (0.53)	-0.56 (0.301)	-0.51 (0.256)	-0.12 (0.746)	-0.51 (0.327)	-0.91 <sup>b</sup> (0.029)
Cluster	District	District	District	District	District	District
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618

Note.

<sup>a</sup> Significant at 1% level.<sup>b</sup> Significant at 5% level.<sup>c</sup> Significant at 10% level.**Table 3**

Estimation of the OLS for six types of stress in the first wave of the pandemic from February to April 2020 in Hong Kong.

Time = 02	(1) stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Road Ratio	0.55 <sup>b</sup> (0.027)	0.51 <sup>b</sup> (0.038)	0.32 (0.187)	0.22 (0.173)	0.28 (0.274)	0.45 <sup>c</sup> (0.061)
Sidewalk	-1.41 <sup>c</sup> (0.025)	-1.01 (0.106)	-1.35 <sup>b</sup> (0.03)	-0.19 (0.66)	-1.37 <sup>b</sup> (0.014)	-1.46 <sup>a</sup> (0.007)
Cluster	District	District	District	District	District	District
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618

Note.

<sup>a</sup> Significant at 1% level.<sup>b</sup> Significant at 5% level.<sup>c</sup> Significant at 10% level.**Table 4**

Estimation of the OLS for six types of stress in the final fifth wave of the pandemic, from February to April 2022 in Hong Kong.

Time = 03	(1) stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Road Ratio	0.909 <sup>a</sup> (0.001)	0.76 <sup>a</sup> (0.005)	0.63 <sup>b</sup> (0.018)	0.29 <sup>c</sup> (0.098)	0.505 <sup>c</sup> (0.064)	0.86 <sup>a</sup> (0.001)
Sidewalk	-0.51 (0.492)	-1.14 <sup>c</sup> (0.063)	-1.05 (0.139)	-0.51 (0.217)	-0.72 (0.351)	-0.69 (0.271)
Cluster	District	District	District	District	District	District
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618

Note.

<sup>a</sup> Significant at 1% level.<sup>b</sup> Significant at 5% level.<sup>c</sup> Significant at 10% level.

identical type 1 extreme value distribution.

Based on the above specification, let  $P_i$  as the probability of residual  $n$  experiencing a mental wellbeing severity level of  $j$ , and then the MNL probability is expressed as:

$$P_i = \frac{e^{\beta x_{nj}}}{1 + \sum_{n=1}^{N-1} e^{\beta x_{nj}}} \quad (3)$$

Marginal effects quantify the alteration in response values that occurs as a result of a one-unit variation in the explanatory variables.

**Table 5**

Estimation of the OLS for six types of stress after the end of the pandemic in Hong Kong.

Time = 04	(1) stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
road ratio	0.909 <sup>a</sup> (0.001)	0.74 <sup>a</sup> (0.005)	0.44 <sup>b</sup> (0.066)	0.38 <sup>b</sup> (0.029)	0.57 <sup>b</sup> (0.029)	0.709 <sup>a</sup> (0.003)
Sidewalk	-0.36 (0.622)	-1.13 <sup>b</sup> (0.068)	-0.86 (0.191)	-0.022 (0.959)	-0.97 (0.136)	-1.01 <sup>b</sup> (0.07)
Cluster	District	District	District	District	District	District
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618

Note: \*\* significant at 5% level.

<sup>a</sup> Significant at 1% level.<sup>b</sup> Significant at 10% level.

In the context of ordinary least squares (OLS) models, these parameters directly represent marginal effects. Conversely, within the framework of the Multinomial Logit (MNL) model, estimated coefficients correspond to the logarithm of odds ratios, as indicated by (Fiebig et al., 2010). To comprehend the outcomes of modeling and grasp the influence of variables within the MNL model, marginal effects can be derived in the following manner:

$$\frac{\partial P_i}{\partial X_j} = e^{\beta x_{nj}\beta'} \left/ \left( 1 + \sum_{n=1}^{N-1} e^{\beta x_{nj}} \right)^2 \right. \quad (4)$$

in the Multinomial Logit (MNL) model, the correlation between the marginal effects and the sign of the coefficients ( $\beta$ ) is not always stable. This is a divergence from certain logit regressions, such as binary logit, where they consistently align. The reason behind this inconsistency stems from the dependence of the marginal effect on the values and levels of other variables. Changes in the values of these variables can result in corresponding shifts in the sign of the marginal effect. In essence, these marginal effects reflect the shift in probability for a given outcome compared to the base level of mental wellbeing level, as discussed in (Shankar & Manner, 1996).

## 5. Results

In our OLS model as the most basic research model, we individually incorporated each built environment variable into the model, alongside the addition of relevant control variables. We have identified a general principle: as the pandemic worsens, the adverse effects of roads on the six types of stress examined in the study are likely to increase. Furthermore, even after the final wave of the pandemic in Hong Kong, the negative impact of road ratio on people's mental wellbeing remains significantly high.

The first period was in the latter half of 2019; it can be inferred that road ratio does have a certain impact on people's mental wellbeing before the pandemic. As the proportion of roads within the street view expands, there is a notable uptick in the occurrences of stress01 (failing getting enthusiastic), stress02 (feeling meaningless of life), and stress06 (overreacting). This pattern suggests a significant relationship between the extent of roads in the street view and these specific stress indicators. However, at this juncture, the proportion of roads in the streetscape does not statistically significantly influence other forms of stress.

As the pandemic unfolded and progressed into its second phase, the proportion of roads to the overall street view continues to exert a statistically significant effect on increasing frequencies of stress01 (failing getting enthusiastic), stress02 (feeling meaningless of life), and stress06 (overreacting). Simultaneously, the statistical significance of the proportion of sidewalk in the street view becomes apparent. With an increased proportion of sidewalks in the street view, there is a discernible decline in the frequencies of stress01 (failing getting enthusiastic), stress02 (feeling meaningless of life), stress 05 (having difficulty to relax) and stress06 (overreacting). This trend is probably attributable to the prolonged periods spent indoors by individuals during the epidemic to evade infection, yet meanwhile there is a burgeoning desire to venture outside and engage with varied external environments via sidewalks.

As our research moves into the third period, the peak of the COVID-19 pandemic in Hong Kong, the impact of the proportion of roads in the streetscape becomes increasingly evident, the variable road ratio is statistically significant for all six types of stress. With the increasing ratio of roads to street view, the frequency of all six stresses also rise to varying degrees. From the perspective of road ratio coefficients, the impact on stress01 and stress06 has even doubled compared to the previous second period. This phenomenon is likely attributed to the fact that, during the peak of the pandemic, most residents experienced a significant reduction in their activity range and were confined to their homes. Consequently, their scope for visual observation was drastically curtailed. This situation led to more frequent visual exposure to dense road networks, potentially heightening feelings of stress.

Upon entering the post-pandemic phase, our study's last period, the proportion of roads within the street view continues to wield a statistically significant influence on the six types of stress. As the proportion of roads within the street view escalates, there appears to be a corresponding upward trend in the occurrence of six types of stress among the residents. Moreover, when examining the coefficients, compared to the peak of the pandemic in the third period, the frequencies of the six stresses triggered by the proportion of roads in the street view have only slightly decreased but still remain high. It can be deduced that residents have yet to fully recuperate from the stress

induced by road ratio throughout the COVID-19 pandemic.

Based on the statistically significant results, we analyze the changing trends of various stress over time. First, for stress 01 (failing getting enthusiastic), in the first period, as the proportion of roads in the streetscape increased by 1 unit, the frequency of stress 01 increased by 0.59 times; in the second period, as the proportion of roads in the streetscape increased by 1 unit, the frequency of stress 01 increased by 0.55 times, which was almost the same as the impact in the first period; in the third period, as the proportion of roads in the streetscape increased by 1 unit, the frequency of stress 01 increased by 0.909 times, which was almost doubled compared with the previous period; the fourth period still had the same impact as the third period, which shows that the impact of the end of the epidemic on stress 01 has not subsided.

Second, for stress 02, during the initial phase, a 1-unit increase in roads within the street view led to a 0.35 unit rise in stress 02 occurrences. In the subsequent phase, a similar increase in road ratio heightened stress 02's frequency by 0.51 times, marking the beginning of the pandemic's exacerbating effects. In the third stage, the same enhancement in road ratio caused stress 02 occurrences to surge by 0.76 times, more than doubling the impact observed prior to the pandemic. Lastly, in the fourth phase, despite a slight reduction, a 1-unit increase in the streetscape's road proportion resulted in a 0.74 unit increase in stress 02 frequency, indicating that the levels of impact, though marginally decreased, remained considerably high.

Third, for stress 06, in the first phase, with every 1-unit increase in the ratio of roads within the streetscape, the occurrence of stress 06 rose by 0.35 times. Moving to the second phase, the same elevation in road ratio led to a 0.45-fold increase in stress 06's frequency, coinciding with the intensifying effects of the pandemic. In the third stage, an identical uptick in the proportion of roads resulted in stress 06's frequency soaring by 0.86 times, more than doubling the pre-pandemic levels. Finally, in the fourth phase, though the impact somewhat lessened, a 1-unit increase in the streetscape's road ratio still caused a 0.709-fold rise in stress 06 occurrences, maintaining an impact level twice that of the period before the pandemic.

These above results illuminate the discernible pattern of street density's influence on the frequency of different types of stress across four distinct time periods. Initially, road ratio asserted its effects prior to the pandemic, with its impact progressively intensifying as the pandemic commenced, continuing to escalate until reaching its zenith during the peak of the pandemic crisis. Following the pandemic's end, the impact of road ratio on stress frequency began to wane, yet it sustained a significant level, remaining considerably elevated in comparison to pre-pandemic conditions.

Meanwhile, our multinomial logit model can also corroborate a positive correlation between road ratio and the frequency of stress. In MNL, we use the dependent variable equal to 1 as our base model. We observe that the marginal effects of all road ratio in the third and fourth time periods are statistically significant when  $y$  equals 0. Moreover, all coefficients related to road ratio exhibit negative values in two periods. This illustrates that as the proportion of roads in the streetscape increases, the meaning of the result represented by dependent variable equal to 0 decreases. In our study, the dependent variable equal to 0 means that stress almost never occurs. Thus, this inversely establishes that an increase in the roads making up the street view correlates with a higher frequency of six forms of stress in two periods.

In general, our research presents a trend indicating that the road ratio does indeed exert a detrimental impact on residents' mental wellbeing in stress from a visual perspective. The advent of the pandemic has further intensified this negative influence, and the stress inflicted by road ratio has not recuperated even after the pandemic. The road ratio continues to pose a severer threat to the mental wellbeing level of residents compared to before the outbreak of the pandemic.

## 6. Discussion

The mental wellbeing of residents will be an important issue to consider in future urban construction and development. In anticipation of future urban development in Hong Kong, it is paramount to design residential areas that minimize encirclement by road networks. By maximizing the presence of parks and green spaces, not only can we enhance the aesthetic appeal of our city, but more importantly, we can mitigate the psychological health concerns prevalent among citizens. Should it prove infeasible for certain communities to avoid dense road grids, a concerted effort must be made to line these roads with lush greenery or erect green barriers. This visual insulation from bustling streets could substantially diminish the sensation of congestion within these areas. Furthermore, the introduction of green barriers holds a dual function. Beyond offering visual relief from the intense road networks, these verdant installations are formidable defenders against pollution and noise—a rampant byproduct of vehicular traffic. Literature corroborates that such pollutants considerably exacerbate psychological distress. By filtering out these detrimental elements, the implementation of green buffers can significantly enhance the quality of life and mental wellbeing resilience of urban dwellers. Meanwhile, such green infrastructure can serve as a sanctuary for biodiversity within the concrete jungle, promoting ecological balance. Additionally, it is critical to accord special attention to the psychological well-being of residents in such high-density road localities. Expanding access to counseling services and facilitating engagements with mental wellbeing professionals can go a long way in elevating the overall mental wellbeing standards across Hong Kong.

## 7. Conclusion

Our study has allowed us to arrive at three salient conclusions that deepen our understanding of the interplay between built environment and mental wellbeing. Firstly, we have observed a clear correlation between the road ratio and their visual impact on the psychological well-being of residents. There is a discernible trend where an upsurge in the proportion of roads within the street view corresponds with an increased frequency of various forms of stress states. This underscores the pressing need for more considerate urban design that balances infrastructural necessities with the mental wellbeing of the community. Secondly, it is evident that the advent of the

COVID-19 pandemic has exacerbated the psychological stress associated with dense road networks. In contrast to pre-pandemic conditions, the omnipresence of roads in the urban landscape has become an even greater contributory factor to the surge in depressive episodes. This phenomenon highlights a newfound exigency for urban planners to introspect and reform the role of thoroughfares in cities, considering their intensified impact during times of crisis. Thirdly, our results indicate that crosswalks potentially possess an ameliorative effect on the prevalence of depression. Particularly in the initial stages of the pandemic, the presence of crosswalks seems to resonate with residents' intrinsic need for mobility and freedom, mitigating feelings of entrapment within their residences. The implication is that creating more opportunities for safe and accessible pedestrian movement could serve as a psychological balm, soothing the urban psyche particularly when larger social freedoms are curtailed.

## 8. Limitations

There are some limitations to this study. The evaluation of mental health is relatively subjective in our analysis, relying on individual questionnaire feedback. Obtaining patient medical records related to mental health would provide a more comprehensive assessment for future research.

Expanding on this limitation, while self-reported questionnaires are commonly used to assess mental health, they can be influenced by individual perceptions, biases, and subjective interpretations. Additionally, self-report measures may not capture the entire spectrum of mental health conditions or provide a complete understanding of the complexities associated with mental well-being. Incorporating medical records and clinical assessments could offer a more objective and comprehensive evaluation of patients' mental health status.

And the primary focus of the study is examining the exacerbating effect of road ratio on mental health during the pandemic. Whether these findings are applicable to other disasters or crises requires further investigation. Building upon this limitation, it is essential to recognize that the impact of road ratio on mental health may vary across different disaster contexts. While this study specifically examines the relationship between road ratio and mental health during the pandemic, it is necessary to conduct additional research to determine if similar patterns exist in other disaster scenarios. Factors such as the nature of the disaster, geographical location, cultural context, and available support systems may influence the psychological impact of different crises. Therefore, future studies should explore and compare the effects of road ratio on mental health in various disaster contexts to provide a more comprehensive understanding of the subject.

### CRediT authorship contribution statement

**Ning Chen:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Xiaodong Chen:** Writing – review & editing, Methodology. **Pengyu Zhu:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization.

### Declaration of competing interest

All authors declare that they have no conflicts of interest.

### Appendix

**Table A1**  
M-logit regression and Marginal effects for M-logit regression

M-logit regression	(1)	(2)	(3)	(4)	(5)	(6)
Time = 1	Stress01	stress02	stress03	stress04	stress05	stress06
<b>Panel A (y = 0)</b>						
Road ratio	−1.14*	−1.06	−0.37	−0.92	0.19	−0.52
	(0.053)	(0.103)	(0.585)	(0.312)	(0.749)	(0.406)
Sidewalk	2.36	1.04	0.54	4.45*	2.71	3.51
	(0.249)	(0.692)	(0.858)	(0.096)	(0.147)	(0.167)
<b>Panel B (y = 2)</b>						
Road ratio	1.005	0.34	0.11	−0.99	0.43	−0.046
	(0.23)	(0.752)	(0.926)	(0.621)	(0.691)	(0.967)
Sidewalk	3.74	−0.47	−1.27	6.66	1.13	3.48
	(0.192)	(0.917)	(0.764)	(0.421)	(0.741)	(0.476)
<b>Panel C (y = 3)</b>						
Road ratio	0.0085	−0.21	1.85	4.12	0.19	3.66**
	(0.995)	(0.99)	(0.317)	(0.115)	(0.883)	(0.027)
Sidewalk	−0.22	1.3	−6.67	52.24***	7	−0.11
	(0.997)	(0.798)	(0.578)	(0.002)	(0.272)	(0.99)
Observations	2626	2624	2623	2621	2621	2620
Marginal effects						
Time = 1	(1)	(2)	(3)	(4)	(5)	(6)

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Table A1 (continued)

	Stress01	stress02	stress03	stress04	stress05	stress06
<b>Panel A (y = 0)</b>						
Road ratio	−0.33** (0.013)	−0.25** (0.048)	−0.098 (0.4)	−0.085 (0.305)	0.022 (0.864)	−0.16 (0.196)
Sidewalk	0.37 0.395	0.23 (0.647)	0.23 (0.637)	0.23 (0.37)	0.43 (0.31)	0.65 (0.199)
<b>Panel B (y = 2)</b>						
Road ratio	0.17** (0.047)	0.076 (0.257)	0.0189 (0.743)	−0.0031 (0.927)	0.021 (0.767)	0.014 (0.818)
Sidewalk	0.29 (0.303)	−0.086 (0.758)	−0.079 (0.637)	0.046 (0.749)	−0.064 (0.781)	0.059 (0.816)
<b>Panel C (y = 3)</b>						
Road ratio	0.013 (0.795)	0.018 (0.666)	0.033 (0.23)	0.011 (0.131)	0.0016 (0.974)	0.079*** (0.01)
Sidewalk	−0.057 (0.774)	0.016 (0.895)	−0.109 (0.544)	0.108*** (0.008)	0.21 (0.396)	−0.535 (0.752)
Observations	2626	2624	2623	2621	2621	2620
M-logit regression						
Time = 2	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
<b>Panel A (y = 0)</b>						
Road ratio	−0.804 (0.228)	−1.02 (0.119)	−0.62 (0.314)	−1.002 (0.188)	−0.68 (0.269)	−0.51 (0.401)
Sidewalk	5.08** (0.014)	−0.62 (0.808)	2.36 (0.362)	1.59 (0.574)	3.01* (0.1)	1.85 (0.412)
<b>Panel B (y = 2)</b>						
Road ratio	0.95 (0.169)	0.8 (0.361)	0.031 (0.97)	−0.71 (0.634)	−0.67 (0.408)	1.61* (0.059)
Sidewalk	−1.005 (0.693)	−4.24 (0.258)	−5.64 (0.113)	0.039 (0.994)	0.92 (0.77)	−1.72 (0.614)
<b>Panel C (y = 3)</b>						
Road ratio	0.42 (0.683)	−0.46 (0.708)	0.78 (0.489)	3.87* (0.087)	1.09 (0.295)	0.18 (0.885)
Sidewalk	1.98 (0.522)	−0.32 (0.937)	8.73* (0.051)	20.66* (0.079)	−2.93 (0.546)	−17.32 (0.08)
Observations	2626	2624	2623	2621	2621	2620
Marginal effects						
Time = 2	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
<b>Panel A (y = 0)</b>						
Road ratio	−0.23* (0.053)	−0.29** (0.032)	−0.17 (0.191)	−0.16 (0.124)	−0.16 (0.234)	−0.23* (0.08)
Sidewalk	1.05*** (0.006)	0.15 (0.76)	0.73 (0.17)	0.102 (0.795)	0.77* (0.079)	0.909* (0.079)
<b>Panel B (y = 2)</b>						
Road ratio	0.22* (0.056)	0.16* (0.054)	0.039 (0.678)	0.0035 (0.944)	−0.053 (0.564)	0.21** (0.013)
Sidewalk	−0.57 (0.191)	−0.42 (0.25)	−0.95** (0.014)	−0.055 (0.706)	−0.04 (0.914)	−0.23 (0.512)
<b>Panel C (y = 3)</b>						
Road ratio	0.29 (0.673)	0.00085 (0.988)	0.062 (0.311)	0.0407** (0.038)	0.108 (0.122)	0.0085 (0.848)
Sidewalk	0.049 (0.81)	0.03 (0.858)	0.48** (0.038)	0.16* (0.059)	−0.31 (0.342)	−0.66** (0.047)
Observations	2626	2624	2623	2621	2621	2620
M-logit regression						
Time = 3	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
<b>Panel A (y = 0)</b>						
Road ratio	−1.12 (0.113)	−1.32** (0.047)	−0.86 (0.117)	−0.98 (0.172)	−1.09* (0.089)	−1.79*** (0.004)
Sidewalk	0.59 (0.808)	−0.46 (0.805)	6.28*** (0.005)	2.87 (0.19)	2.58 (0.177)	0.15 (0.941)
<b>Panel B (y = 2)</b>						
Road ratio	1.16* 0.09	0.88 (0.3)	0.45 (0.567)	0.094 (0.943)	0.63 (0.41)	0.31 (0.695)
Sidewalk	−1.86 0.383	−2.94 (0.412)	3.15 (0.325)	2.54 (0.485)	0.57 (0.849)	−1.52 (0.599)

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Table A1 (continued)

Panel C (y = 3)						
Road ratio	1.43 (0.112)	0.011 (0.991)	1.26 (0.233)	3.14* (0.1)	0.405 (0.679)	1.58 (0.203)
Sidewalk	-0.73 (0.786)	-2.29 (0.496)	6.82** (0.047)	10.79 (0.521)	2.2 (0.438)	-3.16 (0.56)
Observations	2626	2624	2623	2621	2621	2620
Marginal effects						
Time = 3	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Panel A (y = 0)						
Road ratio	-0.34*** (0.004)	-0.4*** (0.004)	-0.29** (0.032)	-0.208* (0.069)	-0.32** (0.017)	-0.5*** (0)
Sidewalk	0.27 (0.528)	0.2 (0.648)	1.07** (0.022)	0.32 (0.376)	0.49 (0.23)	0.21 (0.636)
Panel B (y = 2)						
Road ratio	0.27** (0.023)	0.21** (0.019)	0.11 (0.251)	0.045 (0.471)	0.16* (0.1)	0.15* (0.092)
Sidewalk	-0.39 (0.312)	-0.31 (0.466)	-0.12 (0.772)	0.0054 (0.975)	-0.13 (0.746)	-0.18 (0.567)
Panel C (y = 3)						
Road ratio	0.14* (0.086)	0.043 (0.526)	0.11* (0.1)	0.041** (0.05)	0.062 (0.406)	0.101** (0.041)
Sidewalk	-0.033 (0.879)	-0.11 (0.623)	0.22 (0.292)	0.0903 (0.605)	0.079 (0.715)	-0.12 (0.564)
Observations	2626	2624	2623	2621	2621	2620
M-logit regression						
Time = 4	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Panel A (y = 0)						
Road ratio	-1.706** (0.011)	-1.77*** (0.008)	-0.76 (0.23)	-0.81 (0.277)	-1.28** (0.039)	-1.63*** (0.007)
Sidewalk	3.43 (0.168)	-3.08 (0.225)	0.37 (0.878)	-0.86 (0.747)	-0.101 (0.956)	0.19 (0.931)
Panel B (y = 2)						
Road ratio	1.14 (0.109)	0.36 (0.691)	0.49 (0.59)	2.3* (0.1)	0.37 (0.647)	0.22 (0.804)
Sidewalk	4.67* (0.099)	-6.88* (0.099)	4.8 (0.237)	-0.053 (0.99)	-1.5 (0.657)	-1.07 (0.795)
Panel C (y = 3)						
Road ratio	0.507 (0.599)	-0.31 (0.775)	0.9 (0.481)	1.74 (0.372)	0.66 (0.55)	2.72* (0.1)
Sidewalk	3.103 (0.387)	-3.56 (0.415)	-1.04 (0.838)	-2.64 (0.89)	-2.92 (0.503)	0.062 (0.991)
Observations	2626	2624	2625	2623	2623	2622
Marginal effects						
Time = 4	(1) Stress01	(2) stress02	(3) stress03	(4) stress04	(5) stress05	(6) stress06
Panel A (y = 0)						
Road ratio	-0.45*** (0)	-0.45*** (0.001)	-0.24* (0.074)	-0.22** (0.035)	-0.36*** (0.008)	-0.46*** (0.001)
Sidewalk	0.31 (0.501)	-0.144 (0.79)	-0.18 (0.722)	-0.12 (0.767)	0.16 (0.707)	0.109 (0.831)
Panel B (y = 2)						
Road ratio	0.31*** (0.005)	0.16** (0.05)	0.093 (0.255)	0.12** (0.019)	0.12 (0.177)	0.107 (0.18)
Sidewalk	0.51 (0.251)	-0.505 (0.233)	0.46 (0.209)	0.028 (0.838)	-0.14 (0.704)	-0.11 (0.76)
Panel C (y = 3)						
Road ratio	0.066 (0.374)	0.046 (0.486)	0.054 (0.284)	0.025 (0.229)	0.079 (0.238)	0.11** (0.024)
Sidewalk	0.063 (0.822)	-0.053 (0.84)	-0.076 (0.707)	-0.21 (0.918)	-0.17 (0.53)	0.0024 (0.988)
Observations	2626	2624	2623	2621	2621	2620

**Table A2**

Description of six types of stress

Dependent variable	Description	Question (On average, how often did you have the following situations per week)	Value
STRESS01	Level of stress - frequency of failing getting enthusiastic	feel unable to become enthusiastic about anything	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)
STRESS02	Level of stress - frequency of feeling meaningless of life	feel that life was meaningless	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)
STRESS03	Level of stress - frequency of feeling panic	feeling panic	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)
STRESS04	Level of stress - frequency of having breathing difficulty	experience difficulty breathing (e.g. excessively rapid breathing, breathlessness in the absence of physical exertion)	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)
STRESS05	Level of stress - frequency of having difficulty to relax	find it difficult to relax	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)
STRESS06	Level of stress - frequency of overreacting	tend to overreact to situations	0 = Rarely/Never 1 = Occasionally (1–2 days) 2 = Sometimes (3–4 days) 3 = Always/usually (5+ days)

**Table A3**

Estimation of the OLS for six types of stress in four different periods including all built environment variables

Time = 01	(1)	(2)	(3)	(4)	(5)	(6)
	Stress1	Stress2	Stress3	Stress4	Stress5	Stress6
Road	0.59*** (0.01)	0.35* (0.093)	0.19 (0.298)	0.16 (0.243)	-0.012 (0.956)	0.35* (0.087)
Sidewalk	-0.37 (0.532)	-0.56 (0.301)	-0.51 (0.256)	-0.12 (0.746)	-0.51 (0.327)	-0.91** (0.029)
Building	-0.842 (0.534)	-1.032 (0.415)	0.379 (0.732)	-1.23* (0.099)	-0.49 (0.707)	-1.63 (0.161)
Wall	-2.96 (0.503)	-1.036 (0.843)	0.279 (0.95)	-0.677 (0.854)	-0.52 (0.916)	-0.255 (0.954)
Fence	-12.276 (0.824)	97,493** (0.034)	-68.897* (0.089)	19.299 (0.49)	-27.328 (0.547)	-25.318 (0.543)
Pole	6.868 (0.828)	28.757 (0.333)	5.3 (0.832)	-17.282 (0.237)	-33.731 (0.225)	-33.814 (0.172)
Traffic_light	0.498* (0.089)	0.214 (0.441)	0.2098 (0.381)	0.173 (0.333)	0.296 (0.303)	0.725*** (0.008)
Traffic_sign	1.486 (0.131)	0.131 (0.9)	0.287 (0.764)	0.265 (0.607)	-0.43 (0.697)	0.108 (0.912)
Vegetation	-0.266 (0.549)	-0.286 (0.507)	-0.403 (0.281)	0.181 (0.501)	0.195 (0.651)	-0.024 (0.949)

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Table A3 (continued)

Time = 01	(1) Stress1	(2) Stress2	(3) Stress3	(4) Stress4	(5) Stress5	(6) Stress6
Terrain	1.967 (0.29)	0.997 (0.591)	1.82 (0.238)	0.832 (0.505)	2.96* (0.094)	2.61* (0.1)
Sky	3.315 (0.859)	-34** (0.025)	21.99 (0.113)	-3.724 (0.698)	17.091 (0.265)	13.6 (0.334)
Person	-0.645 (0.746)	0.48 (0.799)	0.334 (0.833)	-0.324 (0.761)	-1.075 (0.584)	-0.252 (0.879)
Rider	-4.059 (0.455)	-0.609 (0.898)	-1.423 (0.729)	-2.69 (0.371)	-2.502 (0.621)	-1.1 (0.799)
Car	-3.375 (0.676)	5.779 (0.509)	-0.235 (0.972)	2.17 (0.665)	-1.617 (0.846)	-2.349 (0.742)
Truck	-6.021 (0.166)	-3.057 (0.47)	-0.465 (0.901)	-1.44 (0.569)	4.645 (0.298)	0.002 (1)
Bus	9.684 (0.603)	8.608 (0.626)	17.158 (0.175)	-4.346 (0.625)	-13.824 (0.297)	-14.182 (0.152)
Train	-43.969 (0.291)	-6.46 (0.88)	-42.922 (0.181)	-24.114 (0.279)	-17.494 (0.7)	-75.398** (0.016)
Bicycle	-0.121 (0.838)	-0.42 (0.428)	-0.137 (0.799)	-0.077 (0.827)	0.156 (0.791)	0.312 (0.573)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618
Time = 02	(1) Stress1	(2) Stress2	(3) Stress3	(4) Stress4	(5) Stress5	(6) Stress6
Road	0.55** (0.027)	0.51** (0.038)	0.32 (0.187)	0.22 (0.173)	0.28 (0.274)	0.45* (0.061)
Sidewalk	-1.41* (0.025)	-1.01 (0.106)	-1.35** (0.03)	-0.19 (0.66)	-1.37** (0.014)	-1.46*** (0.007)
Building	0.168 (0.909)	-0.115 (0.936)	1.62 (0.267)	-1.31 (0.184)	0.128 (0.934)	-1.32 (0.342)
Wall	3.969 (0.416)	4.455 (0.47)	6.28 (0.28)	1.93 (0.676)	8.01 (0.154)	1.267 (0.795)
Fence	-38.779 (0.54)	50.487 (0.431)	-124.83** (0.039)	24.197 (0.581)	-68.11 (0.241)	-67.567 (0.17)
Pole	21.234 (0.52)	20.612 (0.54)	3.04 (0.926)	9.611 (0.635)	-19.06 (0.554)	-69.82** (0.011)
Traffic_light	0.28 (0.381)	-0.034 (0.914)	-0.185 (0.558)	0.303 (0.173)	0.028 (0.931)	0.5* (0.1)
Traffic_sign	1.325 (0.281)	0.511 (0.7)	1.175 (0.343)	0.159 (0.83)	0.517 (0.711)	0.413 (0.684)
Vegetation	-0.84* (0.073)	-0.618 (0.188)	-0.358 (0.47)	-0.103 (0.755)	-0.417 (0.395)	0.096 (0.831)
Terrain	0.544 (0.8)	-1.864 (0.385)	-0.572 (0.794)	0.43 (0.791)	0.422 (0.853)	2.89 (0.12)
Sky	17.197 (0.428)	-20.826 (0.346)	33.669* (0.1)	-5.74 (0.703)	31.471 (0.114)	27.674* (0.092)
Person	0.044 (0.984)	-0.492 (0.828)	1.16 (0.593)	0.221 (0.877)	-1.8 (0.427)	-0.27 (0.895)
Rider	4.079 (0.441)	6.048 (0.272)	-3.88 (0.457)	-4.496 (0.212)	3.11 (0.556)	1.3 (0.784)
Car	5.7 (0.59)	13.683 (0.174)	6.586 (0.452)	2.597 (0.705)	-6.269 (0.514)	-2.34 (0.798)
Truck	-4.722 (0.337)	-3.967 (0.413)	-0.709 (0.88)	-2.41 (0.455)	4.08 (0.426)	1.95 (0.675)
Bus	-19.394 (0.218)	-0.361 (0.983)	20.91 (0.169)	-5.142 (0.689)	-18.122 (0.22)	-9.259 (0.531)
Train	-68.536 (0.125)	-32.77 (0.489)	-79.73** (0.048)	-45.26* (0.073)	-71.9 (0.118)	-101.1*** (0.01)
Bicycle	0.514 (0.454)	0.101 (0.878)	0.674 (0.352)	-0.221 (0.629)	0.185 (0.798)	0.484 (0.483)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618
Time = 03	(1) Stress1	(2) Stress2	(3) Stress3	(4) Stress4	(5) Stress5	(6) Stress6
Road	0.909***	0.76***	0.63**	0.29*	0.505*	0.86***

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Table A3 (continued)

Time = 03	(1)	(2)	(3)	(4)	(5)	(6)
	Stress1	Stress2	Stress3	Stress4	Stress5	Stress6
Sidewalk	(0.001)	(0.005)	(0.018)	(0.098)	(0.064)	(0.001)
Building	-0.51 (0.492)	-1.14* (0.063)	-1.05 (0.139)	-0.51 (0.217)	-0.72 (0.351)	-0.69 (0.271)
Wall	-0.504 (0.755)	-0.75 (0.634)	-0.043 (0.978)	-0.74 (0.501)	-0.53 (0.74)	-3.017** (0.036)
Fence	-6.092 (0.322)	-1.61 (0.801)	-2.24 (0.722)	-0.28 (0.947)	0.677 (0.921)	1.189 (0.843)
Pole	67.95 (0.321)	81.878 (0.227)	-46.366 (0.49)	11.8 (0.798)	-37 (0.587)	-53.2 (0.391)
Traffic_light	35.083 (0.329)	17.856 (0.612)	21.33 (0.555)	-18.31 (0.416)	-50.59 (0.124)	-84.738*** (0.003)
Traffic_sign	0.317 (0.801)	-0.57 (0.6)	0.949 (0.344)	0.046 (0.953)	-0.178 (0.891)	0.446 (0.680)
Vegetation	-0.783 (0.132)	-0.682 (0.176)	-0.29 (0.573)	-0.096 (0.789)	-0.41 (0.416)	0.175 (0.704)
Terrain	0.31 (0.892)	0.251 (0.903)	-0.767 (0.719)	1.103 (0.53)	0.058 (0.98)	1.203 (0.573)
Sky	-9.66 (0.678)	-19.638 (0.397)	20.756 (0.358)	6.71 (0.67)	23.37 (0.306)	28.123 (0.182)
Person	-4.544* (0.063)	-3.18 (0.196)	-2.88 (0.219)	-1.14 (0.479)	-2.68 (0.241)	-2.4 (0.255)
Rider	5.24 (0.367)	10.511* (0.057)	-1.1 (0.828)	-0.359 (0.919)	2.53 (0.65)	0.054 (0.991)
Car	8.95 (0.422)	17.08 (0.118)	15.25* (0.096)	5.1 (0.486)	-1.62 (0.863)	-0.177 (0.984)
Truck	-7.79 (0.144)	-5.92 (0.252)	-2.21 (0.658)	-3.38 (0.356)	0.65 (0.902)	-0.162 (0.974)
Bus	5.378 (0.786)	-0.89 (0.959)	36.59** (0.024)	8.59 (0.506)	12.05 (0.542)	-2.79 (0.876)
Train	-86.11* (0.084)	-47.01 (0.35)	-65.03 (0.151)	-53.78* (0.078)	-81.2* (0.094)	-96.64** (0.027)
Bicycle	0.17 (0.783)	0.268 (0.671)	0.94 (0.159)	-0.36 (0.4)	0.5 (0.456)	0.42 (0.477)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618
Time = 04	(1)	(2)	(3)	(4)	(5)	(6)
	Stress1	Stress2	Stress3	Stress4	Stress5	Stress6
Road	0.909*** (0.001)	0.74*** (0.005)	0.44* (0.066)	0.38* (0.029)	0.57* (0.029)	0.709*** (0.003)
Sidewalk	-0.36 (0.622)	-1.13* (0.068)	-0.86 (0.191)	-0.022 (0.959)	-0.97 (0.136)	-1.01* (0.07)
Building	-0.841 (0.593)	-1.85 (0.233)	0.266 (0.848)	-1.22 (0.244)	-0.18 (0.905)	-2.98** (0.028)
Wall	-0.692 (0.894)	3.2 (0.67)	-0.673 (0.931)	4.02 (0.439)	9.53 (0.169)	4.29 (0.536)
Fence	28.48 (0.669)	37.99 (0.564)	-68.516 (0.266)	-12.57 (0.785)	-74.61 (0.225)	-90.84 (0.132)
Pole	35.6 (0.307)	36.4 (0.327)	25.66 (0.416)	-23.54 (0.28)	-38.02 (0.241)	-79.3*** (0.004)
Traffic_light	0.329 (0.356)	0.281 (0.421)	0.098 (0.746)	0.444* (0.072)	0.37 (0.26)	0.521* (0.083)
Traffic_sign	0.48 (0.678)	-0.714 (0.513)	-0.167 (0.867)	-0.606 (0.436)	-1.304 (0.282)	-0.332 (0.771)
Vegetation	-0.607 (0.227)	-0.417 (0.398)	-0.79* (0.072)	-0.222 (0.525)	-0.627 (0.202)	0.338 (0.449)
Terrain	-1.13 (0.602)	0.95 (0.64)	1.12 (0.568)	1.76 (0.304)	1.058 (0.611)	2.84 (0.168)
Sky	-4.63 (0.838)	-14.34 (0.524)	16.269 (0.433)	5.71 (0.716)	31.702 (0.128)	37.67* (0.066)
Person	-3.99* (0.092)	-1.874 (0.435)	-2.143 (0.285)	-1.15 (0.444)	-3.28 (0.124)	-1.37 (0.474)
Rider	9.46* (0.098)	10.03* (0.071)	1.018 (0.83)	0.248 (0.942)	2.88 (0.585)	0.94 (0.838)
Car	1.75	16.805	3.67	6.02	0.912	3.59

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Table A3 (continued)

Time = 04	(1)	(2)	(3)	(4)	(5)	(6)
	Stress1	Stress2	Stress3	Stress4	Stress5	Stress6
Truck	(0.876) -6.99 (0.168)	(0.12) -9.557* (0.058)	(0.66) -3.21 (0.452)	(0.375) -5.73* (0.082)	(0.922) 0.339 (0.947)	(0.66) -1.76 (0.704)
Bus	-3.42 (0.85)	-7.5 (0.677)	23.397 (0.236)	-10.21 (0.4)	0.406 (0.983)	-10.37 (0.537)
Train	-98.26** (0.036)	-53.45 (0.246)	-21.675 (0.589)	-37.17 (0.193)	-85.14** (0.036)	-89.32** (0.024)
Bicycle	0.203 (0.746)	-0.17 (0.788)	0.77 (0.221)	-0.63 (0.152)	-0.24 (0.732)	0.47 (0.431)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2624	2622	2621	2619	2619	2618

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