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Road Traffic and Urban Form Factors Correlated with the Incidence of Lung Cancer in High-density Areas: An Ecological Study in Downtown Shanghai, China

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Abstract The incidence of lung cancer is affected by air pollution, especially in high-density urban areas with heavy road traffic and dense urban form. Several studies have examined the direct relationship between lung cancer incidence and road traffic as well as urban form. However, the results are still inconsistent for high-density urban areas. This study focused on urban form and road traffic, aiming at revealing their relationship with lung cancer incidence in high-density urban areas at the neighborhood level. For this, an ecological study was conducted in downtown Shanghai to identify important indicators and explore quantitative associations. Negative binomial regression was fitted with lung cancer incidence as the dependent variable. The independent variables included indicators for road traffic and urban form, greenness, demographic, and socio-economic factors. The results showed that building coverage, averaged block perimeter area ratio, density of metro station without the glass barrier system, and the percentage of low-quality residential land were positively correlated with lung cancer incidence in the neighborhood, while population density was negatively correlated with lung cancer incidence. This study found a strong self-selection effect of socio-economic factors in the relationship between lung cancer incidence and greenness. These results may be useful for conducting health impact assessments and developing spatial planning interventions for respiratory health in high-density urban areas.

Keywords Lung cancer · Road traffic · Urban form · High-density urban areas · Health impact assessment

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Introduction

Lung cancer is increasingly attracting research attention because it has the highest incidence among all types of cancer worldwide [1]. Epidemiological studies report that in addition to genetic susceptibility and smoking, ambient air pollution is one of the major risks for lung cancer [2, 3]. The negative impact of air pollution on public health is greater in high-density cities than in less densely populated cities, which may be caused by

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higher emissions resulting from heavy road traffic and the obstruction of air pollutant dispersion due to high building density [4].

The relationship between urban form and air quality has been extensively explored in many empirical studies, which have shown associations between various urban form metrics and air quality at both large-scale between-city level and smaller-scale within-city level [5–9]. Urban form can be quantified through several types of metrics. Building density, population density, and shape complexity have been identified as valid urban form metrics, with the potential to capture these associations [5, 9, 10]. Existing literature generally agrees that building density is negatively correlated with air quality, as large building masses and compact urban massing significantly stagnate airflow and block the dispersion of pollutants from deep street canyons within tall buildings [4, 11, 12]. With regard to population density, results remain inconsistent. Some studies have reported a positive association between population density and air quality [13, 14], while others have found a negative association [15, 16]. In addition to density indicators, the shape of neighborhoods and their complexity and fragmentation in terms of land use may increase vehicle travel time and associated emissions, thereby increasing air pollution levels [16]. However, some recent studies have not identified this association significantly [5, 6].

Several studies have explored the link between urban form and respiratory health. A study in a high-density urban area of Shanghai found that building aspect ratio and frontal area density were significantly associated with mortality from COPD [10]. Another ecological study focusing on the pathways between urban form, air quality, and cardiopulmonary mortality showed that urban density and fragmentation levels have a significant effect on PM2.5 concentrations and, thus, cardiopulmonary mortality at the county level [6]. But few studies have examined the relationship between urban form and lung cancer incidence, especially in high-density urban areas.

Road traffic, the major contributor of ambient air pollution in urban areas, has been investigated in a large body of health-related research [17–21]. Existing research suggests that living near major roads or in areas with high road density increases the risk of lung cancer, asthma, and COPD [22–26]. On the contrary, a convenient public transportation system can reduce motor vehicle travel and thus air pollution [13]. To date, distance thresholds from traffic roads remain uncertain. A study of Los Angeles determined that areas within 300−500 m of major roadways are most affected by traffic emissions [21]. Another study in Delft reported a significant decrease in airborne concentrations of traffic pollutants at 150 m from the road [27]. It is necessary to explore the effect of different distances from the road on respiratory health.

Existing studies generally conclude that urban form and road traffic affect air quality, which then affects the incidence of lung cancer. Better quantitative links between lung cancer incidence and urban form and road traffic are needed to support planning intervention and health impact assessment (HIA). This study, therefore, aims to identify detailed indicators to measure road traffic and urban form which are significantly associated with lung cancer incidence in high-density urban areas. An ecological research design was used with downtown Shanghai as the study site.

Methods

Study Design

To address the research questions of this study, we developed a conceptual framework to describe the factors with potential influences on lung cancer incidence. Figure 1 summarizes the relationship between urban spatial patterns, road traffic, socioeconomic status, and lung cancer. According to previous epidemiological studies, the main risk factors for lung cancer include outdoor and indoor air pollution, smoking, family history, occupational exposure, and diet [28]. Outdoor and indoor air pollution are highly correlated, as PM2.5 generated outdoors is the largest contributor to indoor PM2.5 concentrations [29]. As mentioned earlier, the key linkage of interest was the impact of urban form and road traffic on lung cancer mediated by ambient air pollution. We captured the impact in terms of two pathways corresponding to the built environment—pollution sources and diffusion rates. The main local source of PM2.5 in the highly urbanized area of Shanghai is vehicle exhaust [30]. Its diffusion rates are mainly determined by urban spatial patterns. It is worth noting that green spaces may have a protective effect on respiratory health [31–33]. Therefore, road traffic and urban form factors should be associated with lung cancer incidence after controlling for epidemiological risk

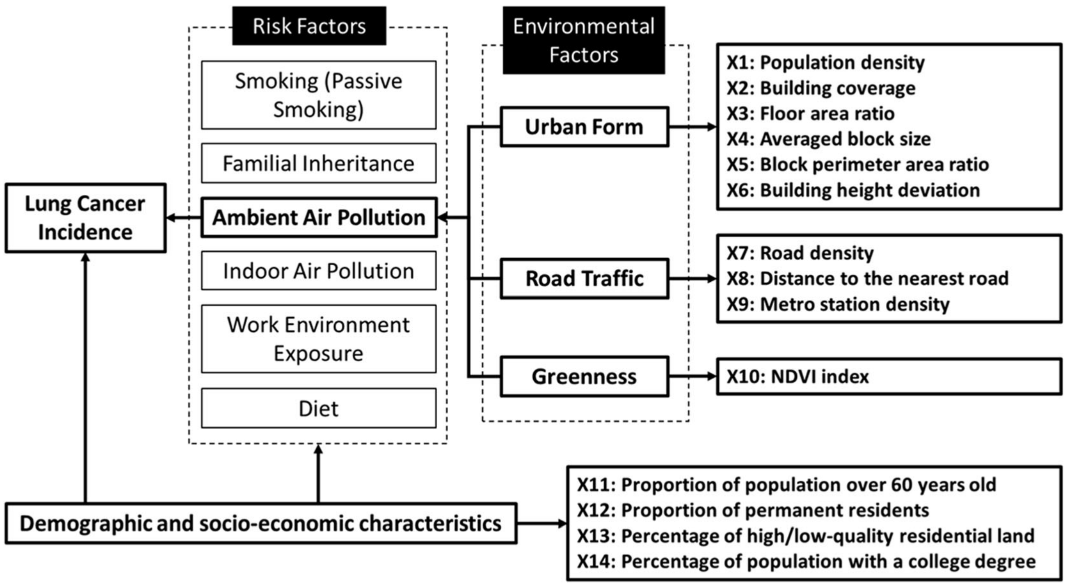

Fig. 1 Conceptual framework of the analysis

factors and greenness. Proxies for road traffic included road density and distance from the nearest main roads. Population density, building density, and variables reflecting urban form complexity were used as proxies for urban form. Normalized Difference Vegetation Index (NDVI) was used as a proxy for greenness. We further employed socioeconomic factors including education level and housing quality to control for smoking and other behavioral and occupational factors to a certain extent. There is considerable evidence that the smoking behavior is strongly associated with education level in China [34–37]. Housing quality is strongly tied to income levels [38]. People living in low-quality houses usually have low the income level and limited accessibility to material and social resources including healthy food and the high risks from occupational exposure [39, 40]. The percentage of high/low-quality residential land and the proportion of population with a college degree was employed as the proxy of housing quality and education level, respectively.

Study Site

The high-density urbanized area of Shanghai, which was also one of the densest urban areas in China, was chosen as the study site. It referred to the area within the Inner Ring Road of Shanghai, with a total area of 115.92 km^2 and a total population of 3.46 million. In this high-density area, the spatial heterogeneity in climate was relatively low. Neighborhoods (census units) consisting of several blocks were used as the geographic units for data aggregation and analysis. There were 958 neighborhoods within the Inner Ring Road of Shanghai. The average area of the neighborhoods was 0.12 km^2.

Dependent Variable: Lung Cancer Incidence

Lung cancer incidence data were obtained from the Shanghai Center for Disease Control and Prevention (SMCDCP). All newly diagnosed lung cancer cases in Shanghai, from January 1, 2009 to December 31, 2013, were reported to SMCDCP by hospitals. The dataset included gender, age, occupation, smoking status, and residential address (permanent address and address of residence for more than 6 months in Shanghai). Using the geocoding tool provided by Baidu Map, lung cancer cases were geo-located on the map based on their residential address and then aggregated into neighborhoods. Thirty-seven neighborhoods were excluded from the analysis because the cases could not be precisely located in these neighborhoods. There were 12,241 male and female lung cancer cases in the high-density area of Shanghai. Raw incidence rates rather than age-adjusted incidence rates were used to represent the risk of lung cancer in the neighborhoods because the population by age group of the neighborhoods was too small to guarantee the stability of the adjustment. In order to mitigate the impact of age structure, the degree of aging was considered in the regression analysis.

Independent Variables

Urban Form

Based on previous studies, variables were used to evaluate urban form in terms of three dimensions including population density, building density, and urban form complexity. Although population density was often used as a variable for holistic urban form at the city level, it was considered to be included in this neighborhood-level study. Population density was calculated by dividing the total population by the total area of the neighborhood.

In terms of building density, we employed building coverage and floor area ratio (FAR) to evaluate the 2D-building density and 3D-building density of the neighborhood, respectively. Building coverage was calculated by dividing the first-floor area of all existing buildings by the total land area of the neighborhood, which reflected the proportion of land occupied by buildings in the area. FAR refers to the total floor area of all buildings divided by the land area of a neighborhood and represents the three-dimensional development volume. Building coverage and FAR are two typical indicators that reflect the intensity of development and can be modified through urban planning.

To measure the complexity of urban form, averaged block size, averaged block perimeter area ratio, and deviation of building height were included in the analysis. This study employed the averaged block size as a measure of the complexity of the neighborhood urban form in terms of texture. Small block size generally implies high road network density and walkability, but may also result in residents being exposed to more motor vehicle traffic pollution. This study employed the averaged block perimeter area ratio as another measure of the complexity of the neighborhood urban form. The block perimeter area ratio reflects the complexity of the block shape, with higher values indicating longer boundaries if the block size remains constant. Further, this study used building height deviations to measure the morphological complexity and diversity of neighborhood buildings in the vertical direction, with higher values indicating a larger building height variation. We expected that the larger variation in building heights could create a better wind field to facilitate the dispersion of pollutants in the neighborhood.

Building density and urban form complexity were calculated using building data of Shanghai in 2015. Although the building data are slightly later than the lung cancer data, there has been little architectural change in most neighborhoods of the study site since the 2000s in Shanghai. Urban renewal had occurred in a few neighborhoods and most buildings had been demolished. We excluded eighteen neighborhoods with building coverage below 10% from the analysis. Sixty-two neighborhoods had a small percentage of residential land use (less than 20%), such as the central business district. They were also excluded from the analysis.

Road Traffic

The variables used to measure the health risks of road traffic as a source of air pollution can be divided into two dimensions: road traffic density and distance. We used road network density as a proxy variable because actual traffic volume was highly correlated with road network density due to high road utilization [41]. Road density refers to the ratio of total road length to the entire land area (km/km^2). Both the total road density and the arterial road density were included in the analysis. Road density was calculated using a total of 15 buffer zones set up within 1500 m with the 100-meter interval to identify the thresholds at which the road traffic affected respiratory health significantly. In terms of the distance dimension, the pollution exposure to heavy traffic roads was characterized by distance to the nearest elevated and arterial roads. The road network data were obtained by vectorizing the 2011 Shanghai Land Use Map on the ArcGIS 10.2 platform.

Furthermore, previous studies reported that high-quality transit service could reduce reliance on motorized transportation and was correlated with reductions in air pollution [13]. So, the density of metro stations in the 800-m buffer zone was used in the analysis as a proxy for public transportation. However, some studies have revealed that subway air has a higher level of iron-containing particulate matter generated from steel rails, power-supply materials, and moving train parts such as wheels and brake pads [42]. The subway air pollution has adverse health effects on passengers especially in the stations without the glass barrier system between the platform and tracks. In light of this, the density of metro stations without the barrier systems was included in the analysis. In particular, Lines 1 and 2 were completed in Shanghai in 1993 and 2000, respectively, and had no barrier systems. Metro stations built after 2009 were not included in the analysis.

Greenness

The Normalized Difference Vegetation Index was employed to measure the greenness of the neighborhoods. The resolution of NDVI data for Shanghai in 2011 was 1 km and was obtained from the Resource and Environment Data Cloud Platform of the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences.

Demographic Characteristic and Socio-economic Status

The proportion of the population over 60 years of age was included in the analysis as a demographic control variable to reduce the confounding effect of neighborhood age structure on the lung cancer incidence. Considering the influence of residential turnover on the measurement of the exposure to the residential built environment, the proportion of permanent residents who have lived for more than 5 years was employed to reflect the stability of the residential population and to adjust the correlation between lung cancer incidence and explanatory variables. Demographic data were obtained from the 2010 Census.

Socioeconomic status is generally assessed by the interdependent dimensions of education, occupation, and income [43]. With the limited socio-economic data, we evaluated the overall socioeconomic status of the neighborhood in two dimensions: housing quality and education level. Housing quality is strongly tied to income levels [38]. The percentage of high/low-quality residential land was employed as the proxy of housing quality. The data on residential land were derived from the 2011 Shanghai Land Use Map. According to its land classification, residential land in Shanghai was divided into 5 different classes based on the quality of housing. In this study, residential land in classes 1–3 was considered high-quality residential land, while class 4 residential land was considered low-quality. The percentage of the population with a college degree was employed to reflect the education level of the neighborhood. The socioeconomic data were obtained from the 2010 Census.

Statistical Analysis

Both Poisson regression and negative binomial regression can be used to fit the discrete count data. Considering that the number of lung cancer cases was an overly dispersed count with variance much greater than the mean, negative binomial regression was used first to explore the effects of road traffic, urban form, and greenness on lung cancer incidence, with socio-economic and demographic factors being controlled. Poisson regression was also considered to fit the data. But the likelihood ratio test showed that the negative binomial model was more appropriate than the Poisson regression model. We performed negative binomial regressions using the following equations:

$$\begin{aligned}\mathrm{Ln}(\mu) = {} & \beta_0 + \beta_1 \text{Urban Form} + \beta_2 \text{Road Traffic} \\ & + \beta_3 \text{Greenness} + \beta_4 \text{Demographic Factors} \\ & + \beta_5 \text{Socioeconomic Factors} \\ & + \mathrm{Offset}(\mathrm{Ln}(\text{Population}))\end{aligned}$$

where μ is the mean of the dependent variable Y. Y is the observed count variable indicating the number of lung cancer cases.

In the preliminary analysis, most of the variables considered in this study were moderately correlated. The strongest correlation (0.71) was between the percentage of high-quality and low-quality residential land. A stepwise regression process, with the goal of minimizing the Akaike information criterion (AIC), was applied to select variables and reduce multicollinearity. In addition, socio-economic variables were included in the models step by step to examine potential self-selection effects. Model 1 included urban form, road traffic, and demographic variables. Model 2 included housing quality and all variables of Model 1, and Model 3 further included education level.

The lung cancer incidence examined in this study had substantial variation at the neighborhood level with a standard deviation of 99/10,000. Considering the possible heterogeneity among gender and age strata in the association between dependent and independent variables [44], we split lung cancer cases into subgroups according to gender (male and female) and age (low-age group: <60, middle-age group: 60–80, and high-age group: >80), and refitted models for each subgroup as a robustness test. We then considered excluding the outliers. An outlier was defined as 3.5 times the standard deviation above the mean. We also fitted models for sub-areas to enhance the robustness of the regression results.

Ln represents the natural logarithm. The incidence rate ratio (IRR), expressed as the exponent of the coefficients in this study, was used to evaluate the relative risk of independent variables. An increase of one unit in the independent variable corresponds to lung cancer incidence rate multiplied by exp(β).

Results

Descriptive Statistics

The characteristics of the 841 neighborhoods in this study and the incidence of lung cancer are shown in Table 1. The area inside the Inner Ring Road of Shanghai was featured with typical high-density, with an average population density of 48,700 people per square kilometer. The average building coverage and the floor area ratio were 32.17% and 2.04, respectively. In addition to the high population and building density, the total road density averaged 12.13 km/km^2, indicating a dense road network. Meanwhile, some variables had a wide range of values, such as the socio-economic factors. The quality of housing was high in some neighborhoods with the percentage of high-quality residential land exceeding 90%, while in other neighborhoods, where the percentage of low-quality residential land exceeded 70%, the quality was low. It is also noteworthy that the proportion of the elderly population (over 60 years old) was very high, with an average value of 20.49%.

The 5-year cumulative incidence of lung cancer of the area inside the Inner Ring Road of Shanghai (35.37/10,000) was higher than that of the whole city of Shanghai (23.37/10,000) [45], indicating a high risk of lung cancer in high-density urban areas.

Model Results

The CoxSnell's pseudo R square for the full model, including all variables, was 0.48, with the AIC at 5,502, indicating that the variables considered in this study explained a high proportion of the variance in lung

Table 1 Variable definition and descriptive statistics (*N*=841)

Factor	Dimension	Variable	Mean	SD	Min	Max
		Lung cancer incidence (cases)	13.45	9.11	0	129
Urban form	Population density	Population density (10^4/km^2)	4.87	2.69	0.04	15.23
	Building density	Building coverage (%)	32.17	11.15	10.27	67.70
		FAR (m^2/m^2)	2.04	0.78	0.41	7.49
	Urban form complexity	Averaged block size (km^2)	0.11	0.10	0.01	0.84
		Averaged block perimeter area ratio (km/km^2)	15.97	5.76	5.70	40.30
		Building height deviation (m)	12.82	8.38	0	48.65
Road traffic	Road density	Total road density (100-m buffer zone, km/km^2)	12.13	3.76	5.54	27.89
		Arterial road density (100-m buffer zone, km/km^2)	1.27	1.44	0	6.29
	Exposure distance	Distance to the nearest elevated road (km)	0.96	0.72	0.05	3.05
		Distance to the nearest arterial road (km)	0.34	0.24	0	1.21
	Public transport services	Metro station density (800-m buffer zone, #/km^2)	0.64	0.32	0	1.58
		Density of metro station without the glass barrier system (800-m buffer zone, #/km^2)	0.16	0.26	0	1.10
Greenness	Green space coverage	NDVI index	0.24	0.06	0.13	0.54
Demographic factors	Aging level	Proportion of population over 60 years (%)	20.49	4.85	5.33	38.68
	Residential turnover	Proportion of permanent residents (living for more than 5 years, %)	72.37	14.17	0	100
Socio-economic factors	Housing quality	Percentage of high-quality residential land (%)	37.44	22.34	0	93.43
		Percentage of low-quality residential land (%)	11.66	17.28	0	78.29
	Education level	Percentage of population with a college degree (%)	32.05	14.42	3.94	72.16

cancer incidence (see Appendix Table 3 for coefficients). The fits of the increasingly complex series of models were improved with the inclusion of socio-economic factors step by step (Table 2). The final stepwise model (Model 3) had a CoxSnell's pseudo R square of 0.47 and an AIC of 5,492.

Regarding urban form factors among the independent variables, the population density was negatively correlated with lung cancer incidence, with a relative risk of 0.93 (95%CI: 0.915–0.946). Building coverage and the averaged block perimeter area ratio were positively correlated with lung cancer incidence, with a relative risk of 1.009 (95%CI: 1.004–1.014) and 1.008 (95%CI: 1.001–1.015), respectively. The building height deviation and floor area ratio were negatively associated with lung cancer incidence but became insignificant with the inclusion of socio-economic factors.

In considering road traffic factors, the density of the metro station without the glass barrier system was positively correlated to lung cancer incidence with a relative risk of 1.206 (95%CI: 1.044–1.395), while the total metro station density was insignificant. Distance to the nearest arterial road was significant at the beginning, but it was no longer significant when the education level entered the

Table 2 Results of the stepwise regression model (*N*=841)

[a]Variable	Model 1		Model 2		Model 3	
	[b]IRR (95%CI)	P value	IRR (95%CI)	P value	IRR(95%CI)	P value
Urban form						
Population density	0.926(0.910,0.943)	0.000***	0.927(0.911,0.943)	0.000***	0.930(0.915,0.946)	0.000***
Building coverage	1.022(1.016,1.028)	0.000***	1.012(1.007,1.018)	0.000***	1.009(1.004,1.014)	0.000***
FAR	0.887(0.820,0.961)	0.003**				
Averaged block size	1.620(0.980,2.708)	0.075+	1.461(0.894,2.411)	0.153		
Averaged block perimeter area ratio	1.017(1.007,1.027)	0.001**	1.016(1.006,1.026)	0.002**	1.008(1.001,1.015)	0.032*
Building height deviation	0.992(0.983,1.001)	0.071+	0.986(0.980,0.991)	0.000***		
Road traffic						
Distance to the nearest elevated road	1.042(0.987,1.101)	0.131				
Distance to the nearest arterial road			0.831(0.709,0.976)	0.024*		
Arterial road density (100-mbuffer zone)	1.029(1.001,1.058)	0.041*			1.022(0.995,1.049)	0.107
Density of metro station without the glass barrier system	1.230(1.053,1.438)	0.008**	1.291(1.112,1.500)	0.001**	1.206(1.044,1.395)	0.010**
Greenness						
NDVI index	0.083(0.034,0.201)	0.000***	0.137(0.057,0.329)	0.000***		
Demographic factors						
Proportion of population aged over 60 years	1.020(1.010,1.029)	0.000***	1.027(1.017,1.036)	0.000***	1.028(1.019,1.038)	0.000***
Proportion of permanent residents (living for more than 5 years)	1.007(1.004,1.010)	0.000***	1.007(1.004,1.010)	0.000***	1.005(1.002,1.008)	0.011*
Socio-economic factors						
Percentage of low-quality residential land			1.010(1.008,1.013)	0.000***	1.008(1.005,1.011)	0.000***
Percentage of population with a college degree					0.981(0.977,0.985)	0.000***
Model summary						
Pseudo R square (CoxSnell)	0.38		0.42		0.47	
AIC	5577.2		5534		5485.4	

[a] Only variables retained by the stepwise regression process were listed in the table

[b] Incidence Rate Ratio

***p<0.001; **: p<0.01; *: p<0.05; +:p<0.1

model. Neither total road network density nor arterial road network density was not significant for any buffer zones in the final stepwise regression model (Model 3).

The NDVI index was significantly and negatively associated with lung cancer incidence in Model 1, and remained significant when controlling for the percentage of low-quality residential land (Model 2). However, the correlation between the NDVI index and the incidence of lung cancer became insignificant when further controlling for the education level (Model 3).

Unsurprisingly, the aging level was significantly and positively correlated with lung cancer incidence. The proportion of permanent residents also showed a significant and positive correlation, suggesting that the more people who have lived for more than five years, the higher lung cancer incidence. Regarding socio-economic factors, the percentage of low-quality residential land was significantly and positively correlated with lung cancer incidence, with a relative risk of 1.008 (95%CI: 1.005–1.011). The percentage of the population with a college degree was significantly and negatively correlated with lung cancer incidence, and explained the largest proportion of the variance in lung cancer incidence (26%).

Robustness Check

We ran additional models to check the robustness of the regression results. We first fitted models for subgroups, including male and female, as well as low, middle, and high age groups. Figure 2 depicts the relative risk (incidence rate ratio and its 95% confidence interval) of the independent variables retained by a stepwise regression process for the different groups. Population density, building coverage, and percentage of low-quality residential land were significantly correlated with lung cancer incidence for all sub-groups. The density of the metro station without the glass barrier system was significantly correlated with lung cancer incidence except for the high age group.

Meanwhile, we excluded outliers (3.5 times standard deviation above the mean) and re-fitted the models for the whole study area. The results showed that the fit of the model had a significant improvement and the pseudo R square increased to 0.67. In addition to all significant variables of the model using the full dataset, the total road density in the 100-m buffer zone presented a significant and positive correlation with lung cancer incidence in the model of which the outliers were excluded (see Appendix Table 4).

We also fitted models for two sub-areas of downtown Shanghai, *Puxi* (the western area of the Huangpu River) and *Pudong* (the eastern area of the Huangpu River). The former was a traditional high-density urban area, while the latter had become a newly developed high-density urban area since the 1990s. Compared with models fitted for the whole study area, the model fit was slightly reduced for *Puxi*, whereas it was significantly improved for *Pudong* (see Appendix Tables 5 and 6). The pseudo R square was 0.62 and 0.75 of the *Puxi* and *Pudong* model, respectively. Building coverage, aging level, housing quality, and education level remained significant for both sub-areas. The total road density was only significant for *Puxi*. The population density was negatively and significantly correlated with lung cancer incidence in *Puxi*, while a positive Pearson correlation was observed in *Pudong*.

Discussion

The ecological analysis was designed to investigate the quantitative association between lung cancer incidence and the road traffic and urban form factors in high-density urban areas at the neighborhood level. There are several findings from this study.

First, urban form affects lung cancer incidence in multiple pathways in high-density urban areas. Among the variables measuring urban form, building coverage shows a significant and positive correlation with lung cancer incidence, while floor area ratio shows a negative but insignificant correlation. The computational fluid dynamics simulations of the wind environment usually show that an increase of the building coverage decreases the mean wind velocity ratio, and that the average pedestrian-level wind velocity can be explained well by the building coverage ratio rather than by the floor area ratio [10, 46]. This study confirms this argument by incorporating respiratory health outcomes affected by wind speed and further supports a causal pathway relationship from building coverage, wind speed, and pollutant dispersion to lung cancer incidence.

Reflecting the complexity of the block shape, the block perimeter area ratio shows a positive and significant correlation with lung cancer incidence. The block perimeter area ratio presents a larger value in the neighborhood with a longer block boundary and smaller block size. Considering that the block size has been controlled in the regression, the positive linkage

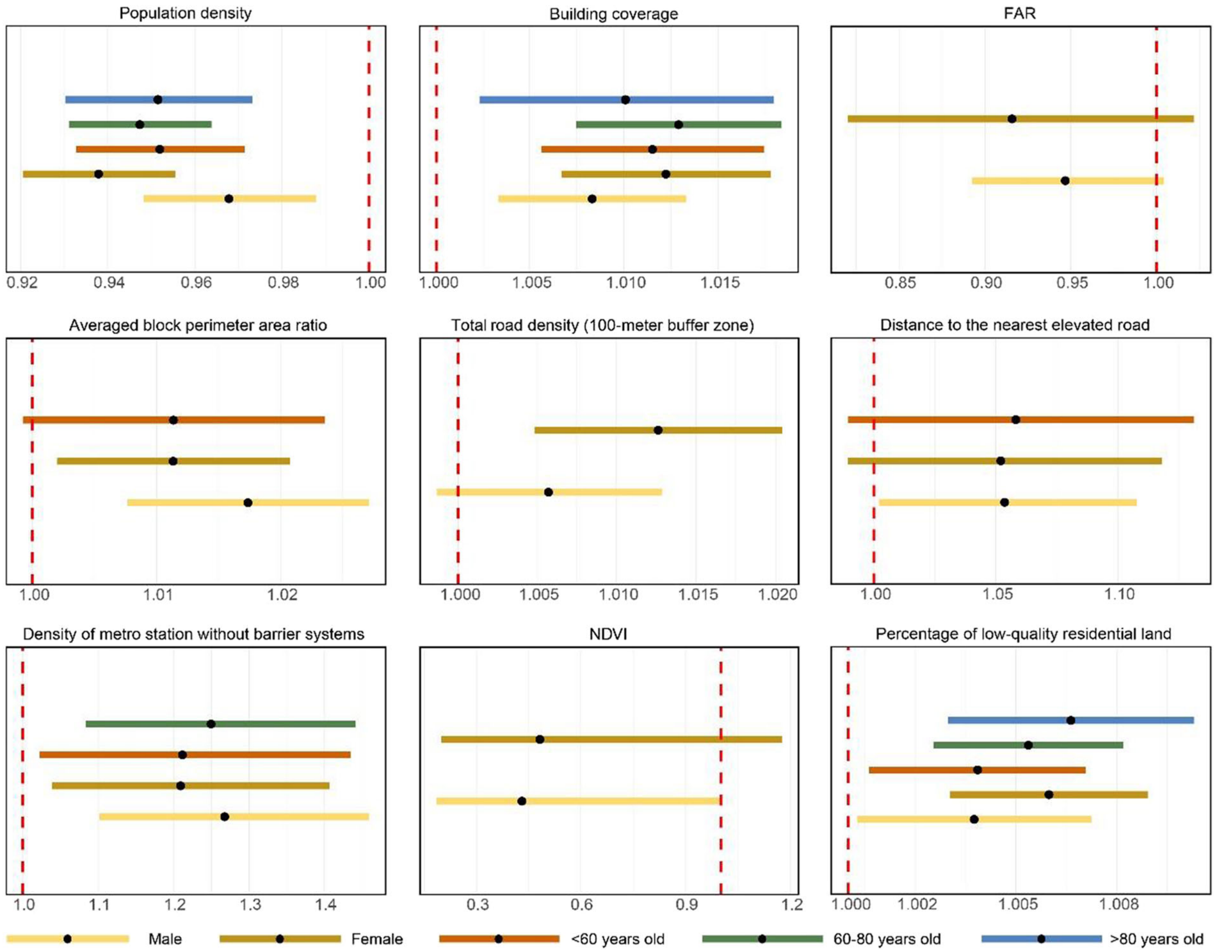

Fig. 2 Relative risk (incidence rate ratio and 95% confidence interval) of independent variables for different gender and age groups

between block perimeter area ratio and lung cancer incidence indicates that a too zigzag block shape may be detrimental to residents' respiratory health. This is consistent with existing literature reporting that urban shape complexity has the potential to increase air pollution levels as it may increase the vehicle travel time and its associated emissions [16]. It is also worth noting that the small block size contributes to the high perimeter area ratio and correlates with lung cancer incidence negatively [47]. This suggests that in high-density urban areas, the planning model advocating small blocks may bring more exposure of local residents to traffic-related pollution and then harm their respiratory health.

Furthermore, population density has been widely used to reflect the holistic characteristics of urban form, but studies on its relationship with lung cancer incidence are insufficient. Most of existing studies are conducted in the context of the urban–rural continuum. These studies have found a positive correlation between population density and lung cancer incidence, the explanation behind which is that traffic-related air pollution presents more severe in densely populated areas [48–51]. However, we find a negative and robust correlation between population density and lung cancer incidence in the context of the completely urbanized and high-density area. This study, therefore, supports the comparable view that high population density may reduce per capita emissions by reducing reliance on cars and travel distances while low-density development areas are undersupplied with jobs and public service facilities, thus generating more motorized trips [5, 52, 53]. An interesting finding of this study is that population density is negatively correlated with lung cancer incidence in *Puxi*, whereas it is positively Pearson correlated with lung cancer incidence in *Pudong*. Disparities in public service facilities at the neighborhood level may explain the variation in the correlation between population density and lung cancer incidence in the two sub-areas. The more densely populated neighborhoods in *Puxi* have more amenities and less need for motorized travel, whereas in *Pudong*, even very densely populated neighborhoods have inadequate amenities, leading to more motorized travel.

Second, road and traffic factors may play a role in influencing the incidence of lung cancer. We find a significant but not robust association between traffic road and lung cancer incidence, possibly due to the strong correlation among road density and distance variables. The total road density is positively and significantly associated with lung cancer incidence after excluding the outliers. This is consistent with previous studies that living in an area with high road density contributes to a higher risk of developing respiratory disease [21, 27]. However, we are unable to identify robust thresholds at which road distance may affect respiratory health in the high-density area, which is subject to further exploration by future studies.

A new finding of this study is that the density of metro stations without the glass barrier system between the platform and tracks is positively and significantly correlated with lung cancer incidence after controlling for other variables. Recent studies have found that employees working on the subway platforms, where PM concentrations are the greatest, tended to have higher levels of risk markers for cardiovascular disease than ticket sellers and train drivers [54]. To date, however, there is little clear epidemiological evidence of abnormal respiratory health effects on underground workers and commuters. Our study shows a robust and high risk for lung cancer in neighborhoods of high-density urban areas around the metro stations without the glass barrier system. The elevated light rail stations without the glass barrier system are also included in the analysis, but no significant risks for lung cancer are observed in neighborhoods around these stations. Meanwhile, there are significantly high risks for different gender and age groups except for the high age group, possibly due to the low frequency of the subway use by the elderly. Therefore, the respiratory health of passengers waiting on underground metro platforms may be seriously influenced, especially in stations without the glass barrier system between the platform and tracks. Considering that the metro lines that have not adopted the glass barrier system are usually constructed at an earlier time and have more interchange stations, their adverse health impacts may not be limited to the area along the metro line but extend to other areas. The monitoring of air quality in metro stations should be strengthened and actions should be taken to reduce air pollution in metro stations.

Third, we find that education level is the most relevant factor for the incidence of lung cancer and has a strong self-selection effect in the relationship between lung cancer incidence and built environment factors such as NDVI index and building height deviation, measuring greenness and the diversity of urban form, respectively. The NDVI index and building height deviation become no longer significant after including education level in the model. This indicates that residents with a higher level of respiratory health tend to live in neighborhoods with more green spaces and a combination of high-rise and low-rise buildings. Although our study is unable to ascertain whether NDVI index and building height deviation have a direct influence on lung cancer incidence, the need remains to improve health equity especially for neighborhoods with low socio-economic status. Besides, more longitudinal studies are needed to overcome the potential self-selection bias and explore the health impact of greenness and the diversity of urban form.

Finally, the lower housing quality may contribute to a higher risk of lung cancer. We find that lung cancer incidence is higher in neighborhoods with a higher percentage of low-quality residential land or a lower percentage of high-quality residential land. This is consistent with the results of previous empirical studies and reviews [55–57] and is possible because people living in low-quality residential areas may have high smoking rates and unhealthy diets due to the self-selection effect. However, the percentage of low-quality residential land remains significant, even after controlling for education level. This indicates that relatively poor environmental and housing quality in low-quality residential areas may cause poor respiratory health outcomes, because the low housing quality usually implies small living space, worse ventilation conditions, and often no separate kitchen [58, 59], which may lead to high exposure to kitchen fumes.

Limitations

The first limitation of this study is its reliance on an ecological research design. Ecological studies cannot be used to make causal inferences between dependent and independent variables [60]. In addition, ecological studies are often confronted with ecological fallacies and a Modifiable Areal Unit Problem (MAUP). Nevertheless, this study is still valuable in that it reveals a quantitative relationship between lung cancer incidence and multiple built environment variables and explains a high proportion of variance, supporting the development of health impact assessments in high-density areas.

Second, we are unable to incorporate the latency of lung cancer in the analysis due to the lack of the earlier built environment data. We would argue that the land use data in 2011 and the building data in 2015 could basically reflect the built environment since 2000, about 10 to 15 years ago. There was a policy announced by Shanghai municipal government in 2000 to decrease the demolishing and redevelopment in downtown Shanghai, the study site in this paper. In particular, the annual average increase in floor area was less than 10% after 2005, according to Shanghai Urban Construction Statistical Yearbook. Meanwhile, we employed the proportion of permanent residents who had lived for more than 5 years as a control variable to ensure at least 5 years of exposure in Shanghai. So, using environmental data from the same time period of lung cancer data or even slightly later has limited influence on the validity of the results in this study. It is for sure that the results could be more precise when better data are available.

Third, the current study is limited by the lack of data on smoking, diet, and occupational exposure. According to the literature, education level and housing quality included in this study shall represent the risks from smoking and other behavioral and occupational factors to a great extent. We, therefore, assume that there would no systematic error between the selected proxies and the real data. The random error generated because of the absence of data on smoking, diet, and occupational exposure at the neighborhood level does exist. It might increase the standard error of the estimated coefficients and widen its 95% confidence intervals, but have limited influence on the reliability of our conclusions. Future study may consider to conduct tobacco, occupation, and diet survey at the neighborhood level to better control for smoking, occupational exposure, and diet factors.

A further limitation of the study is that it lacks consideration of human daily mobility and then has a neighborhood effect averaging problem (NEAP) [61]. The neighborhoods in the study area are quite small in size, so most people would travel outside their residential neighborhood and are exposed to air pollution when undertaking their daily activities (e.g., commuting, workplaces) [62]. This study attempts to mitigate this problem by fitting models for different gender and age groups with different daily mobility characteristics. The associations between the incidence of lung cancer and urban form factors remain significant for the older age group (>80 years of age) that usually undertakes daily activities within the neighborhood. Nevertheless, ignoring the effect of people's dynamic exposure may still have some influence on the results. Future studies may consider including exposures outside the neighborhood in the analysis.

Conclusion

Using the dataset with a total of 12,241 lung cancer cases and an ecological research design, this study identifies important urban form and road traffic factors in high-density areas and their quantitative relationship with lung cancer incidence. The findings are obtained with a high degree of model fit and robustness and can be applied to health impact assessment and spatial planning intervention in other high-density urban areas. More longitudinal studies should be conducted to clarify the causal associations between respiratory health and road traffic as well as urban form.

This study has several implications for urban planning. There is a need to focus on and reduce health inequities of lower socio-economic neighborhoods, especially for those with high building densities, small green spaces, or low housing quality. Urban renewal can be undertaken to reduce building coverage and create more open and green spaces in high-density urban areas. It is not recommended to adopt the currently popular small-block planning model in urban development which has been widely implemented in high-density urban areas. It requires the decrease of automobile traffic in the small-block planning to avoid the high exposure of traffic-related air pollution. Finally, it is necessary to consider appropriate protective measures of respiratory health for residents who frequently take the metro, e.g., by adding a barrier system between the platform and tracks and improving ventilation systems.

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Appendix

Table 3 Results of the regression model with all variables (N=841)

Variable	IRR	95% Confidence Interval		P-value
		Lower limit	Upper limit	
Urban form				
Population density	0.924	0.905	0.943	0.000***
Building coverage	1.009	1.003	1.016	0.005**
FAR	0.997	0.916	1.085	0.942
Averaged block size	1.351	0.829	2.221	0.253
Averaged block perimeter area ratio	1.01	0.999	1.02	0.073+
Building height deviation	0.998	0.988	1.007	0.597
Road and traffic				
Total road density (100-meter buffer zone)	1.001	0.992	1.011	0.77
Arterial road density (100-meter buffer zone)	1.015	0.972	1.061	0.499
Distance to the nearest elevated road	1.035	0.98	1.093	0.211
Distance to the nearest arterial road	0.951	0.763	1.187	0.656
Metro station density (800-meter buffer zone)	1.044	0.922	1.182	0.495
Density of metro station without the glass barrier system (800-meter buffer zone)	1.22	1.04	1.431	0.014*
Greenness				
NDVI index	0.475	0.186	1.217	0.109
Demographic factors				
Proportion of population over 60 years	1.028	1.019	1.038	0.000***
Proportion of permanent residents (living for more than 5 years)	1.005	1.002	1.008	0.011*
Socio-economic factors				
Percentage of low-quality residential land	1.008	1.005	1.012	0.000***
Percentage of high-quality residential land	1.001	0.998	1.004	0.485
Percentage of population with a college degree	0.983	0.978	0.988	0.000***
Model summary				
Pseudo R square: 0.48 (CoxSnell), 0.48 (Nagelkerke), 0.09 (McFadden) and 0.37 (sqPearson)				
AIC: 5496.8				

***: p<0.001, **: p<0.01, *: p<0.05, +:p<0.1

Table 4 Results of the stepwise regression model (outliers excluded, N=831)

Variable	IRR	95% Confidence Interval		P-value
		Lower limit	Upper limit	
Urban form				
Population density	0.949	0.935	0.963	0.000***
Building coverage	1.01	1.005	1.014	0.000***
Averaged block size	1.443	0.943	2.217	0.102
Averaged block perimeter area ratio	1.008	1.000	1.017	0.066+
Road and traffic				
Total road density (100-meter buffer zone)	1.007	1.000	1.014	0.037*
Distance to the nearest elevated road	1.039	0.993	1.088	0.101
Density of metro station without the glass barrier system (800-meter buffer zone)	1.233	1.085	1.401	0.001**
Greenness				
NDVI	0.565	0.262	1.222	0.14
Demographic factors				
Proportion of population over 60 years	1.047	1.039	1.055	0.000***
Socio-economic factors				
Percentage of low-quality residential land	1.006	1.004	1.008	0.000***
Percentage of population with a college degree	0.983	0.98	0.986	0.000***
Model summary				
Pseudo R square: 0.67 (CoxSnell), 0.67 (Nagelkerke), 0.15 (McFadden) and 0.51 (sqPearson)				
AIC: 5178.3				

***: p<0.001, **: p<0.01, *: p<0.05, +:p<0.1

Table 5 Results of the sub-area stepwise regression model with outliers excluded (Pudong, N=126)

Variable	IRR	95% Confidence Interval		P-value
		Lower limit	Upper limit	
Urban form				
Building coverage	1.023	1.002	1.045	0.029*
Road and traffic				
Density of metro station without the glass barrier system (800-meter buffer zone)	1.993	1.29	3.088	0.002**
Demographic factors				
Proportion of population over 60 years	1.062	1.03	1.096	0.000***
Socio-economic factors				
Percentage of low-quality residential land	1.017	1.003	1.031	0.01*
Percentage of population with a college degree	0.988	0.978	0.997	0.013*
Model summary				
Pseudo R square: 0.75 (CoxSnell), 0.76 (Nagelkerke), 0.20 (McFadden) and 0.57 (sqPearson)				
AIC: 705.27				

***: p<0.001, **: p<0.01, *: p<0.05, +:p<0.1

Table 6 Results of the sub-area stepwise regression model with outliers excluded (Puxi, N=706)

Variable	IRR	95% Confidence Interval		P-value
		Lower limit	Upper limit	
Urban form				
Population density	0.941	0.927	0.956	0.000***
Building coverage	1.012	1.007	1.018	0.000***
FAR	0.931	0.864	1.003	0.059+
Averaged block size	1.391	0.915	2.123	0.135
Averaged block perimeter area ratio	1.008	0.999	1.016	0.091+
Building height deviation	1.007	0.998	1.015	0.127
Road and traffic				
Total road density (100-meter buffer zone)	1.005	0.999	1.012	0.124
Density of metro station without the glass barrier system (800-meter buffer zone)	1.138	0.997	1.299	0.054+
Demographic factors				
Proportion of population over 60 years	1.04	1.031	1.05	0.000***
Socio-economic factors				
Percentage of low-quality residential land	1.006	1.003	1.008	0.000***
Percentage of population with a college degree	0.983	0.979	0.987	0.000***
Model summary				
Pseudo R square: 0.62 (CoxSnell), 0.62 (Nagelkerke), 0.13 (McFadden) and 0.48 (sqPearson)				
AIC: 4466.4				

***: p<0.001, **: p<0.01, *: p<0.05, +:p<0.1

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