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Research Article

Quantifying the contribution of activity patterns to $PM_{2.5}$ exposure inequity between urban and rural residents by a novel method

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Abstract

$PM_{2.5}$ pollution variations in different microenvironments would result in $PM_{2.5}$ exposure inequity between rural and urban residents. In this study, the real-time $PM_{2.5}$ exposure of urban and rural residents in China was examined based on portable $PM_{2.5}$ sensors together with activity patterns derived from questionnaire surveys, with a focus on students and senior citizens who are sensitive to air pollution. The results showed that $PM_{2.5}$ exposure varied significantly among different resident groups, with higher $PM_{2.5}$ exposure of rural residents than those of urban residents. $PM_{2.5}$ exposure peaks mostly occurred during (Accompanied) cooking activities owing to strong emissions. Sleeping and resting were the main activities that affected $PM_{2.5}$ exposures of different resident groups, accounting for 60.7%–94.5% of total daily exposures. Furthermore, the long duration of sleeping makes it the predominant activity contributing to $PM_{2.5}$ exposure inequity. It is necessary to obtain point-to-point respiratory volume (respiratory rate) data when measuring real-time $PM_{2.5}$ exposure data and incorporate respiratory volume (respiratory rate) into the analysis of $PM_{2.5}$ exposure. For the first time, this study quantified the $PM_{2.5}$ exposure inequality based on a novel method and can provide useful information for further studies on the exposure inequity.

Keywords

$PM_{2.5}$ exposure
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1 Introduction

Environmental inequity commonly occurs across numerous countries and demographic groups. Usually, people living in developing countries with low income have less access to clean water, food, and air, resulting in more series health outcomes. Air pollution is still a main concern for human health around the world, especially in developing countries with poor air quality. It's estimated that more than 6.7 million premature deaths were caused by air pollution globally, of which about 89% occurred in low and middle-income countries (WHO 2022). The inequity of air pollution exposure has been of great concern in the last few years since people exposed to poorer air may have a higher risk of various respiratory diseases, cardiovascular diseases, and mortality (Deng et al. 2021; Zhou et al. 2023). However, most previous studies discussed environmental inequity of air pollution exposure based on ambient air

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List of symbols

A_x	activity pattern	i	number of individuals
$C_{j\text{-PM}_{2.5}}$	$PM_{2.5}$ concentration at data monitoring point j (μg/m^3)	j	data monitoring point of portable sensors
D_{IE}	$PM_{2.5}$ exposure difference between urban and rural resident groups	m, n	total number of data monitoring points of portable sensors
$D_{\mathrm{IE(Breath)}}$	$PM_{2.5}$ exposure difference after considering respiratory volume between urban and rural resident groups	M	rural or urban
$D_{\mathrm{IE(Breath)}\text{-}A_x}$	exposure difference after considering respiratory volume between urban and rural resident groups under the activity pattern A_x	N	sample number of each resident group
$D_{\mathrm{IE}\text{-}A_x}$	$PM_{2.5}$ exposure difference between urban and rural resident groups under the activity pattern (A_x)	p_{A_x}	proportion of respiratory volume (respiratory rate) from other activity patterns compared to sleeping
D_{M_i}	daily exposure concentrations of individual i in each resident group (μg/m^3)	R_{A_x}	contribution of a certain activity pattern (A_x) to the $PM_{2.5}$ exposure inequity
E_{M_i}	cumulative daily exposure to pollutants (μg·s/m^3)	t	data monitoring interval of the portable sensor (20 s)
		T_{M_i}	time proportion of an activity pattern (A_x)
		V_{A_x}	respiratory volume (respiratory rate) of the activity pattern A_x

pollution level, ignoring the contribution of air pollution exposure in indoor microenvironments such as offices, schools, and kitchens (Colmer et al. 2020; Jbaily et al. 2022). However, people usually stay in a variety of microenvironments, and the air quality in different indoor sites usually varied significantly due to the differences in emission sources and indoor/outdoor air exchange rates (Wang et al. 2023a). For instance, the daily $PM_{2.5}$ concentration in the kitchen could be as high as 338 μg/m^3, much higher than that in the living room (246 μg/m^3), bedroom (275 μg/m^3), and outdoor air (152 μg/m^3) (Du et al. 2018; Yang et al. 2021). Some recent studies also confirmed such large space variation in various microenvironments using real-time monitors (Shen et al. 2021; Wang et al. 2023a). Thus, it is crucial to use the exposure concentration based on different microenvironments and/or activity patterns to accurately characterize the inequity of air pollution exposure.

In particular, there are significant differences in $PM_{2.5}$ exposure between rural and urban residents caused by income level, geographical location, population size, and other factors. $PM_{2.5}$ exposure in low-income countries is significantly higher in rural areas than that in urban areas (Lim et al. 2022). For example, low-income households in India suffered from a higher risk of premature death due to indoor air pollution, which was mainly caused by solid fuel use (Rao et al. 2021). Also, Lim et al (2016) found that the individual $PM_{2.5}$ exposure of senior citizens in rural Asan was higher than that in urban Seoul and higher indoor air pollution in rural homes was confirmed as the dominant reason. However, previous studies usually use household income and education level to explain environmental inequity (Milojevic et al. 2017), seldom focus on exposure differences between rural and urban residents and explore the initial driving factors of environmental inequity (Luo et al. 2022). Individuals generally engage in a variety of daily activities that take place in distinct microenvironments, such as sleeping in the bedroom, cooking in the kitchen, and studying in school. Each environment has its unique air quality, which can significantly impact the overall exposure to pollutants for the residents. However, to date, no available study has investigated the influences of the activity patterns in different microenvironments on the inequity of air pollution exposure.

In this study, portable sensors were used to monitor real-time $PM_{2.5}$ exposure of rural and urban residents with special foci on senior citizens and school children, who are more sensitive to air pollution (Peled 2011; He et al. 2016; Dong 2017; Gouveia et al. 2018). A detailed survey on the activity patterns was recorded, thus the contribution of different activity patterns to $PM_{2.5}$ exposure of urban and rural residents can be discussed accordingly. The main objectives of this study are: (1) to describe the real-time $PM_{2.5}$ exposure of urban and rural residents with special foci on senior citizens and school children; (2) to explore the contribution of activity patterns to the daily $PM_{2.5}$ exposure; (3) to investigate the contribution of activity patterns to the inequity of air pollution exposure between senior citizens and school children based on a novel method. For the first time, this study considers the contribution of different activity patterns to the inequity of air pollution exposure between urban and rural residents, and the results can provide helpful information for policymakers and academics.

2 Materials and methods

2.1 $PM_{2.5}$ exposure measurement and information collection

The field study was conducted in the summertime (June), in Mianyang City, Sichuan Province. In this study, we focused on air pollutant exposure of school children and senior citizens who are more sensitive to $PM_{2.5}$ pollution and the difference between rural and urban residents (Figure S1 in the Electronic Supplementary Material (ESM) of the online version of this paper). Therefore, senior citizens and school children in rural and urban areas were randomly recruited depending on their willingness. Portable $PM_{2.5}$ sensors were distributed to volunteers, and the operation method was trained by researchers. Volunteers were asked to carry $PM_{2.5}$ sensors for at least 24 hours, and $PM_{2.5}$ sensors could be placed nearby within 1.0 m only when sleeping or using the restroom. The samples which did not last one day were discarded (N = 12). For samples that last more than one day, we retained the data from the start time to the same time point in the next day (exactly 24 h). The $PM_{2.5}$ sensor used in this study is designed for real-time exposure monitoring with the advantage of portability, and each sensor is equipped with a laser scattering sensor (Plantower PMS7003, Beijing, China) and powered by a button battery. This sensor fits well with the foci of this study due to its advantages including low cost, portability, no need for electricity plug-in, and more flexibility in choosing where to place compared with the monitors used in previous studies (Chen et al. 2020; Du et al. 2021, Shen et al. 2021, Wang et al. 2023b).

Along with the $PM_{2.5}$ exposure monitoring, a questionnaire was filled out by researchers. Information on the activity pattern was derived from a face-to-face interview that recorded the activity patterns of the residents, including the type of microenvironments in which residents stayed and the corresponding duration. In addition to the activity pattern, information on the cooking fuel, gender, and age was also recorded (Table S1 in the ESM). Finally, 50 elementary students (7–12 years old) including 27 in rural areas and 23 in urban areas, and 36 senior citizens (over 55 years old) including 18 in rural areas and 18 in urban areas were recruited in the field measurement.

2.2 Quality control and data analysis

Before the field campaign, $PM_{2.5}$ monitors were calibrated for at least 15 days against a particulate matter monitor (model 5030 synchronized hybrid ambient real-time particulate monitor, Thermo Scientific) with R^2 > 0.92 (Figure S2 in the ESM), and the calibration methods can be found elsewhere (Huang et al. 2022; Li et al. 2022; Wang et al. 2023b). Previous studies have shown that exposure measurements are influenced by various factors, including indoor and outdoor pollutant concentrations, ventilation conditions, behavioral activities, and so on (Hodas et al. 2016; Huang et al. 2017; Du et al. 2018). Adjustments were made for potential confounders in the exposure measurements, such as completing the campaign in only several days to mitigate the impact of meteorological conditions. Based on the real-time $PM_{2.5}$ exposure and the activity patterns recorded by the questionnaire, we identify the accurate duration that each volunteer stayed in each microenvironment. The activity patterns in different microenvironments were recorded as kitchen for cooking (senior citizens) and accompanied cooking (school children), living room for resting, bedroom for sleeping, outdoor for walking, school for studying, and car for commuting.

Equation (1) was used to calculate the cumulative daily exposure of individuals as:

$$E_{M_i} = \sum_{j=1}^{n} \left(C_{j\text{-PM}_{2.5}} \times t \right) \tag{1}$$

The daily exposure concentration of individuals under the activity pattern A_x was calculated by Equation (2):

$$E_{M_i - A_x} = \sum_{j=1}^{m} \left(C_{j\text{-PM}_{2.5}} \times t \right) \tag{2}$$

where E_{M_i} is the cumulative daily exposure of pollutant (μg·s/m^3); M_i is R_i (Rural) or U_i (Urban) depends on the resident groups calculated; i means the number of individuals; $C_{j\text{-PM}_{2.5}}$ means the $PM_{2.5}$ concentration at data monitoring point j (μg/m^3); n and m are the number of data monitoring points of portable sensors; t is the data monitoring interval of portable sensor (20 s).

Thus, the daily exposure concentrations of individuals could be calculated by Equation (3) and the daily average exposure concentration of residents could be calculated by Equation (4).

$$D_{M_i} = E_{M_i} / (t \times n) \tag{3}$$

$$D_M = \sum_{i=1}^{N} D_{M_i} / N \tag{4}$$

where D_{M_i} is the daily exposure concentrations of individual i in each resident group (μg/m^3); D_M is the daily average exposure concentration of each resident group (μg/m^3), N is the sample number of each resident group.

The daily average exposure concentrations of individuals under activity pattern A_x could be calculated by Equation (5), and the daily average exposure concentrations of residents under activity pattern A_x could be calculated by Equation (6).

$$D_{M_i-A_x} = \frac{E_{M_i-A_x}}{t \times m} \times T_{M_i} \tag{5}$$

$$D_{M-A_x} = \sum_{i=1}^{N} D_{M_i-A_x} / N \tag{6}$$

where $D_{M_i-A_x}$ is the daily exposure concentrations of individual i under activity pattern A_x (μg/m^3); T_{M_i} is the time proportion of the activity A_x; D_{M-A_x} is the daily average exposure concentration of each resident group under activity pattern A_x (μg/m^3).

The time proportion of activity A_x was calculated by Equation (7):

$$T_{M_i} = t_{A_x} / 86400 \tag{7}$$

where t_x is the total time of activity A_x (s); 86,400 is the total time in a day (s).

The $PM_{2.5}$ exposure inequity between rural and urban resident groups was defined by Equation (8) and Equation (9):

$$D_{\mathrm{IE}} = D_{\mathrm{R}} - D_{\mathrm{U}} \tag{8}$$

$$D_{\mathrm{IE}\text{-}A_x} = D_{\mathrm{R}\text{-}A_x} - D_{\mathrm{U}\text{-}A_x} \tag{9}$$

where D_{IE} is the $PM_{2.5}$ exposure difference between urban and rural resident groups, and $D_{\mathrm{IE}\text{-}A_x}$ is the exposure difference between urban and rural resident groups under the activity pattern A_x.

When considering differences in respiratory volume (Table S2 in the ESM) for different activities, the $PM_{2.5}$ exposure inequity between rural and urban resident groups was defined by Equation (10) to Equation (12):

$$p_{A_x} = \frac{V_{A_x}}{V_{\mathrm{sleeping}}} \tag{10}$$

$$D_{\mathrm{IE(Breath)}\text{-}A_x} = D_{\mathrm{R}\text{-}A_x} \cdot p_{\mathrm{R}\text{-}A_x} - D_{\mathrm{U}\text{-}A_x} \cdot p_{\mathrm{U}\text{-}A_x} \tag{11}$$

$$D_{\mathrm{IE(Breath)}} = \sum D_{\mathrm{IE(Breath)}\text{-}A_x} \tag{12}$$

where $D_{\mathrm{IE(Breath)}}$ is the $PM_{2.5}$ exposure difference after considering respiratory volume between urban and rural resident groups, and $D_{\mathrm{IE(Breath)}\text{-}A_x}$ is the exposure difference after considering respiratory volume between urban and rural resident groups under the activity pattern A_x. V_{A_x} is the respiratory volume of the activity pattern A_x. p_{A_x} is the proportion of respiratory volume from other activity patterns compared to sleeping.

To estimate the contribution of different activity patterns to the $PM_{2.5}$ exposure inequity for a certain resident group, an index R is defined by Equation (13):

$$R_{A_x} = D_{\mathrm{IE}\text{-}A_x} / D_{IE} \tag{13}$$

where R_{A_x} is the contribution of a certain activity A_x to the $PM_{2.5}$ exposure inequity.

The estimation of D_M and $D_{\mathrm{IE}\text{-}A_x}$ is conducted by Monte Carlo simulation (the detailed description of the method can be seen in Supplementary Materials in the ESM). Numerical operations were randomly selected based on the data distribution and 10,000 runs were performed to obtain the final simulation results (Hu and Zhao 2022).

Exposure data was logarithmically processed. Kolmogorov-Smirnov test was used to assess the normality of data. The frequency distribution of the data was tested by skewness and kurtosis. Based on the distribution data, $PM_{2.5}$ exposure was found to follow a lognormal distributions. One-way ANOVA test was employed to compare the $PM_{2.5}$ exposure concentration among six resident groups. The least significant difference (LSD) method was used to perform the pairwise comparisons of group mean. Statistical analysis was conducted using SPSS 21.0 software (IBM Corporation, Armonk, NY, USA), and $p < 0.05$ was used as the statistical significance level.

3 Results and discussion

3.1 The description of activity patterns of rural and urban residents

Table 1 provides the detailed activity patterns of different resident groups. According to the different types of urban and rural volunteers, residents are divided into six categories: rural student on holiday (RSH), urban student on holiday (USH), rural student in school (RSS), urban student in school (USS), rural senior citizen (RSC) and urban senior citizen (USC). A total of six patterns of activity are identified: resting, sleeping, (Accompanied) cooking, walking, studying, and commuting. Among them, resting, sleeping, (Accompanied) cooking, commuting, and studying are indoor activities, while walking is an outdoor activity. Resting, sleeping, and walking are the common activity patterns of all resident groups. Studying is a unique activity for students in schools in urban and rural areas. Commuting is an activity that only exists in urban residents. There is no (Accompanied) cooking activity for urban students in school due to urban students usually live on campus, where their lunch and dinner are served. In contrast, rural students generally go home to eat and help the adults prepare food in the kitchen on school days, thus (Accompanied) cooking activity is observed for rural students. The result here shows the distinct patterns of the microenvironment-activity of different resident groups.

Exposure to environmental air pollutants is largely dependent on time-microenvironment-activity patterns of different resident groups (Schweizer et al. 2007; Dons et al. 2011). Human tracks can represent the movement of people among places with different air exposure levels (Ma et al. 2021). Therefore, the variation in activity patterns may cause the differences in $PM_{2.5}$ exposure of urban and rural residents to a certain extent. Table 1 summarizes the duration of different resident groups in various microenvironments. It can be observed that the exposure time of resting and sleeping accounts for more than 70% of all resident groups and even more than 90% of the students on holiday. Although the duration of (Accompanied) cooking is relatively short, the contribution of this activity pattern cannot be ignored since the $PM_{2.5}$ concentration in the kitchen is much higher due to cooking. The duration of different activities also varied for each paired group (e.g., RSH vs USH, RSS vs USS, and RSC vs USC). For example, the duration of resting for RSC is 30.9%, significantly lower than that for USC (35.2%). Similarly, the duration of walking for RSH is much lower than that for USH (2.7% vs 8.3%). Figure 1 provides the $PM_{2.5}$ exposure concentrations of all residents under different activity patterns. The fact that SD of $PM_{2.5}$ exposure concentrations under some activities is larger than the mean value could be found in Figure 1. The reason is that in this group, some samples are not involved in certain activities. For example, 61% of members in RSH group did not take part in the (Accompanied) cooking activity. It's observed that in most cases, the exposure concentrations of rural residents are significantly higher than that of the paired urban residents, which will cause the inequity of $PM_{2.5}$ exposure between rural and urban residents.

3.2 The real-time $PM_{2.5}$ exposure of rural and urban residents

The daily average $PM_{2.5}$ exposure is calculated based on real-time data, and the results can be seen in Figure 2. For each paired group, the daily average $PM_{2.5}$ exposure of rural residents was significantly higher than that of urban residents ($p < 0.05$). $PM_{2.5}$ exposure concentrations were slightly higher for students on holiday than for those in school

Table 1 Classification of activity patterns of urban and rural residents and average exposure time ratio under different activity patterns

	Resting	Sleeping	(Accompanied) Cooking	Walking	Studying	Commuting
RSH	50.1%	46.1%	1.0%	2.7%	—[a]	—
USH	44.8%	45.3%	0.7%	8.3%	—	0.8%
RSS	17.2%	43.0%	0.6%	12.7%	26.4%	—
USS	12.0%	45.4%	—	17.7%	24.7%	0.3%
RSC	30.9%	49.7%	5.1%	14.3%	—	—
USC	35.2%	44.2%	5.8%	14.4%	—	0.3%

Note: RSH: rural student on holiday, USH: urban student on holiday, RSS: rural student in school, USS: urban student in school, RSC: rural senior citizen, USC: urban senior citizen.

[a] The activity duration for the group is 0.

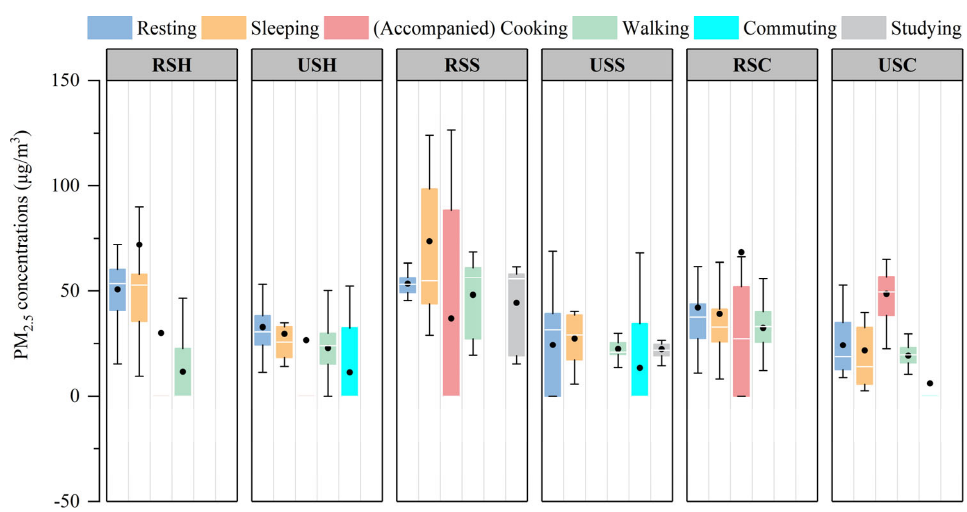

Fig. 1 $PM_{2.5}$ exposure concentration of urban and rural residents under different activity patterns. The upper edge of the box, median bar, and lower edge of the box represent the 75th, 50th, and 25th percentiles, respectively. Upper and lower error bars indicate that values are in the nonoutlier range. "•" represents mean concentration

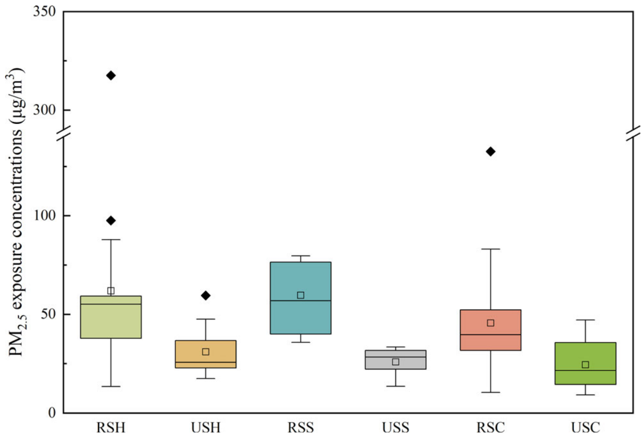

Fig. 2 Daily average PM$_{2.5}$ exposure concentrations of urban and rural residents. The upper edge of the box, median bar, and lower edge of the box represent the 75th, 50th, and 25th percentiles, respectively. Upper and lower error bars indicate that values are in the nonoutlier range. "□" represents mean concentration. "◆" represents outliers

(61.96 ± 55.02 vs 59.92 ± 21.74 μg/m^3 in rural, and 30.93 ± 11.08 vs 25.85 ± 6.77 μg/m^3 in urban), but there was no significant difference ($p > 0.05$). This is because students in school spent about 40% of their time in classrooms with lower PM$_{2.5}$ concentrations, whereas students on holiday are more likely to stay in living rooms and bedrooms, which have higher PM$_{2.5}$ concentrations. In rural China, residents usually use solid fuels (fuelwood, coal, etc.) for cooking, which will increase indoor PM$_{2.5}$ concentration due to the strong internal emissions to a certain extent (Wang et al. 2023b). For urban residents, the use of clean fuels (natural gas and electricity) can effectively reduce indoor PM$_{2.5}$ concentrations (Li et al. 2022). All the investigated residents in this study spend most of their time indoors, thus the high PM$_{2.5}$ concentrations in the indoor environments can contribute significantly to their daily exposures (Wyss et al. 2016; Vardoulakis et al. 2020). Therefore, indoor PM$_{2.5}$ pollution should be paid more attention from the perspective of human health protection.

As seen in Figure 2, several outliers are observed in RSH, USH, and RSC. According to the recording of questionnaires, the two outliers in RSH (317.66 μg/m^3 and 97.61 μg/m^3) are caused by the high exposure concentrations during sleeping when incense burning (Huang et al. 2022). The outlier of RSC (132.55 μg/m^3) is derived from the high exposure concentrations during cooking.

To better illustrate the contributions of different activity patterns to PM$_{2.5}$ exposure, real-time data combined with activity pattern information is used. Figure 3 shows the typical samples of 24-hour real-time PM$_{2.5}$ exposure of six resident groups. Significant differences in real-time PM$_{2.5}$ exposure are observed among six resident groups under different activity patterns. For each paired group, 24-hour real-time PM$_{2.5}$ exposure (except for peaks) of rural residents is higher than that of urban residents. This contrast is most pronounced when sleeping, PM$_{2.5}$ exposure concentration during sleeping for rural residents ranges from 20 to 80 μg/m^3, higher than that of urban residents (from 5 to 23 μg/m^3). The PM$_{2.5}$ exposure peaks (value where PM$_{2.5}$

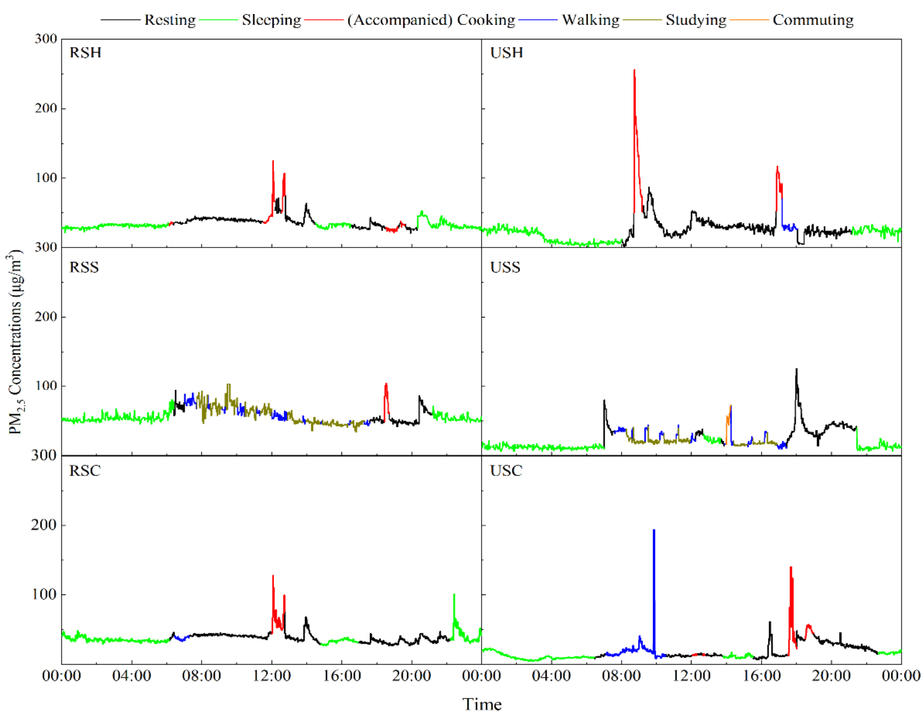

Fig. 3 24-h real-time PM$_{2.5}$ exposure of typical urban and rural residents under different activity patterns

concentration significantly increases) of the residents mostly occur when (Accompanied) cooking, except for USS. This is attributable to that cooking activity can emit considerable $PM_{2.5}$, and can rapidly increase $PM_{2.5}$ concentration in the kitchen (Zhao and Zhao 2018; Zheng et al. 2022).

Apart from significant exposure peaks during cooking time, $PM_{2.5}$ exposure peaks are also observed in all resident groups when resting in the living room, which may be caused by the occasional smoking activity. The real-time $PM_{2.5}$ exposure data can provide new insight into risk assessment. Some exposure assessment studies use daily average exposure concentration to assess the short-term health effects of $PM_{2.5}$, which can lead to the extremely high exposure time being ignored, thus resulting in an unreliable estimate of exposure (Manigrasso et al. 2013; Buonanno et al. 2014). Some studies have found a significant association between health assessment outcomes and $PM_{2.5}$ exposure even when individuals are at a lower daily average exposure level (<10 μg/m^3) (Shi et al. 2016; Lin et al. 2018). Furthermore, even people who live in the same family may have different short-term outcomes due to varied activity patterns. Therefore, the combination of real-time exposure and activity patterns may generate more accurate results when assessing the health effects of $PM_{2.5}$.

3.3 The contribution of different activities to $PM_{2.5}$ exposure

People generally stay in various microenvironments for different activity patterns and are exposed to air pollutants in the corresponding microenvironments. Figure 4 shows the contribution of different activity patterns to daily $PM_{2.5}$ exposure for the investigated resident groups. Compared with all other activities, sleeping and resting contribute primarily to $PM_{2.5}$ exposure (ranging from 32.8% to 49.3% and from 14.2% to 47.2%, respectively). This result confirms that resting and sleeping play a decisive role in $PM_{2.5}$ exposure due to the relatively longer duration that residents spend in their bedrooms and living rooms. The contribution of resting for school children is significantly lower than that of other groups, because most of their time is spent studying in the classroom, and the time spent in the living room is correspondingly reduced. The contributions of studying $PM_{2.5}$ exposure are 20.5% and 22.7% for RSS and USS groups, respectively, indicating the significant concern about indoor air quality in school. When factoring in respiratory volume, a notable shift in the contribution of each activity pattern to $PM_{2.5}$ exposure was observed (Figure S3 in the ESM). The contribution of sleeping, resting, and studying to $PM_{2.5}$ exposure decreased, while activity patterns with higher respiratory volumes (such as (Accompanied) cooking, walking, and commuting) showed a significant increase in the contribution to $PM_{2.5}$ exposure. The primary sources of $PM_{2.5}$ exposure also varied among different resident groups (cooking for senior citizens and walking for students in school). Therefore, future studies should include respiratory volume (respiratory rate) in accessing $PM_{2.5}$ exposure by synchronizing the measurement of respiratory volume (respiratory rate) with real-time $PM_{2.5}$ exposure data.

The contribution of (Accompanied) cooking to $PM_{2.5}$ exposure shows a significant difference between students and senior citizens (Figure 4, $p < 0.05$). In most investigated homes, senior citizens are responsible for cooking, while students only stay in the kitchen intermittently and do not participate in cooking activities. Moreover, cooking-generated

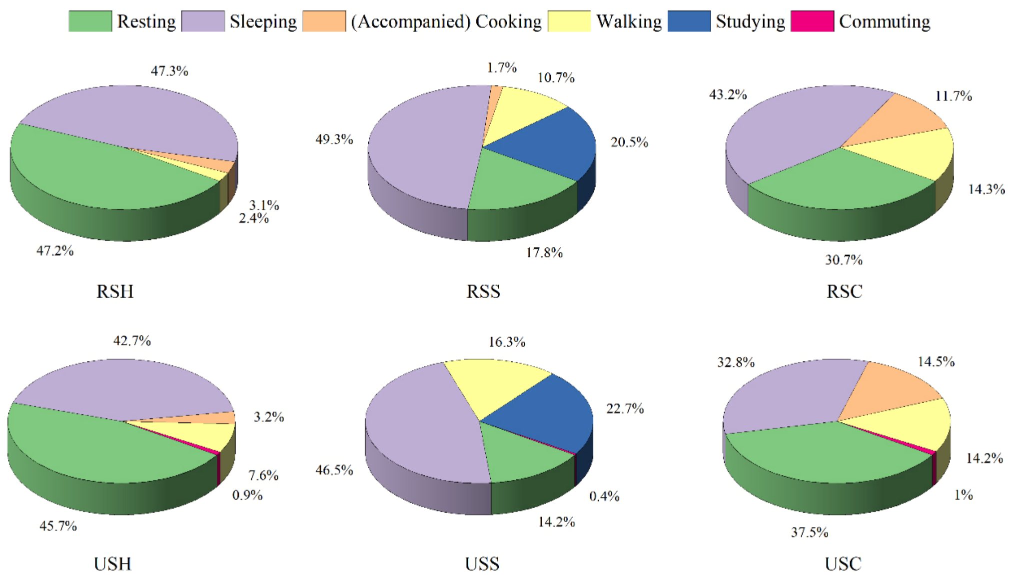

Fig. 4 The contribution of different activities to $PM_{2.5}$ exposure of urban and rural residents

particles in indoor environments are likely to remain long after cooking activities. The proportion of time spent cooking was 1.0% for students and 6.0% for senior citizens, while the contribution of cooking to $PM_{2.5}$ exposure was 3.2% for students and 14.5% for senior citizens. Therefore, the contribution of (Accompanied) cooking to $PM_{2.5}$ exposure should be paid attention to, especially for senior citizens due to higher exposure risk. Both long periods of low $PM_{2.5}$ concentration and short periods of high $PM_{2.5}$ concentration significantly affect $PM_{2.5}$ exposure (Buonanno et al. 2014). The $PM_{2.5}$ exposure from walking shows a tendency that senior citizens have a higher contribution from walking than students (14.25% in senior citizens vs 13.5% in students in school vs 5.0% in students on holiday). Commuting is a unique activity pattern of urban residents, and its contribution to the daily $PM_{2.5}$ exposure is less than 1.0% due to its relatively shorter duration.

3.4 The contribution of different activities to $PM_{2.5}$ exposure inequity

Based on the measured $PM_{2.5}$ concentration and recorded activity patterns, the contributions of different activities to $PM_{2.5}$ exposure inequity are calculated based on the novel method described in the method section. As seen in Figure 5, apart from commuting and walking, the contributions of other activities to $PM_{2.5}$ exposure inequity between USH and RSH groups are higher than 0, indicating that rural students have higher exposure risk under most activities than urban students.

Walking had a positive contribution to $PM_{2.5}$ exposure inequality in Student-School and Senior-Citizen groups because outdoor $PM_{2.5}$ exposure concentrations were higher in rural than in urban areas, and both groups spent similar amounts of time outdoors in rural and urban areas (12.7% vs 17.7% and 14.3% vs 14.4%, respectively). On the contrary, the negative contribution in Student-Holiday can be attributed to the fact that rural students seldom spend time outdoors during holiday (2.7% in rural vs 8.3% in urban). Sleeping contributes most to $PM_{2.5}$ exposure inequity with 50%, 54%, and 43%, respectively, due to the long duration of sleeping among all investigated activities (43.0%–49.7%) and the fact that rural bedrooms have higher indoor $PM_{2.5}$ levels.

For other paired groups, the contributions of most activities are higher than 0, mainly because rural residents rely on traditional solid fuels for daily cooking, resulting in significantly higher $PM_{2.5}$ concentration in rural households than in urban households (Yang et al. 2021; Luo et al. 2022). After considering the respiratory volume (Figure 5(b)), $PM_{2.5}$ exposure inequity for Student-Holiday changes greatly (49% vs 94% for resting, 50% vs 77% for sleeping, and −23% vs −70% for walking). For the other groups, the contribution of sleeping is reduced, and cooking is elevated. Therefore, it is necessary to consider the respiratory volume as a factor, and future studies need to consider the corresponding activities of the population based on the exposure concentration. It should be noted that various toxic components of $PM_{2.5}$ generated from solid fuel burning such as organic carbon, polycyclic aromatic hydrocarbons, and heavy metals (Alves et al. 2017; Chen et al. 2017; Lai et al. 2019) can pose a threat to human health, especially for children and senior citizens. Fullerton et al. (2008) revealed that low birthweight, cataracts, cardiovascular events, and all-cause mortality both in adults and children are also associated with pollutants emitted from solid fuel combustion. Therefore, the $PM_{2.5}$ exposure inequity needs to be paid attention to between rural and urban residents.

3.5 Implication and limitation

Environmental inequity caused by different environmental exposure levels and activity patterns can result in different health outcomes among people with different racial/ethnic or socioeconomic statuses (such as income, occupation, and education) (Bell and Ebisu 2012; Luo et al. 2022). For

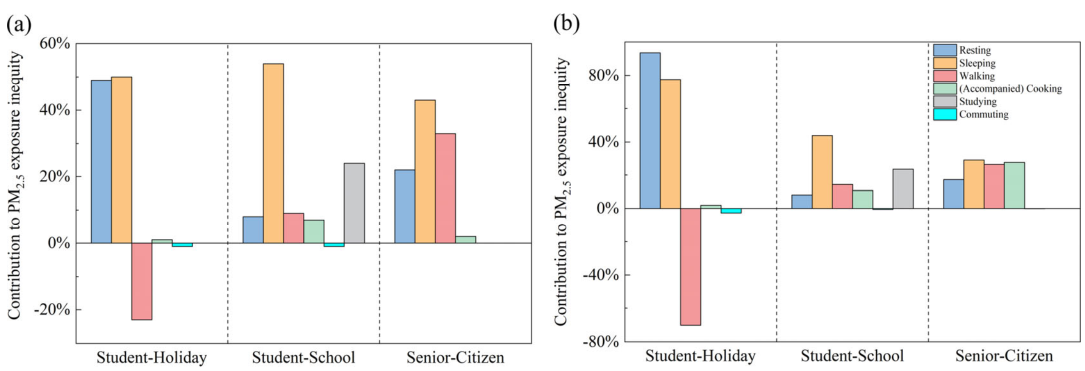

Fig. 5 The inequity contributions of $PM_{2.5}$ exposure between urban and rural residents under different activity patterns: (a) without respiratory volume; (b) with respiratory volume

example, Miranda et al. (2011) reported that non-Hispanic blacks and people over 64 years of age have higher exposure to $PM_{2.5}$ than other Americans. Residents with low income tend to be exposed to higher concentrations of air pollution (Milojevic et al. 2017). However, most previous studies usually focused on comparing exposure concentrations and analyzing the effects of different socioeconomic factors on inequity (Brainard et al. 2002; Chuai et al. 2021; Harvard et al. 2009; Jerrett et al. 2001; Kirby-McGregor et al. 2023), which can not quantify the contribution of activity pattern (Table S3 in the ESM). This study quantified the contribution of different activities to exposure inequity using a novel method with the input of high temporal resolution data and activity pattern, which can provide a scientific basis for targeted reductions in air pollution control in the future.

Nowadays, the air quality gap between urban and rural areas in China is still significant, and common in other developing countries. It's crucial to quantitatively describe the environmental inequity caused by air pollution exposure, especially considering the multiple microenvironments the residents stayed and the corresponding activity patterns, to provide more information for policymakers and the academic community. This study provides a novel method for estimating the contribution of different activity patterns to the $PM_{2.5}$ exposure inequity, highlighting the important contribution of cooking activity and higher indoor air pollution in rural homes. This method is believed to have great potential in future studies for the estimation of other paired resident groups. However, there are still some limitations that should be noted. First, given the high cost of field measurement, the sample size is relatively small. Second, only school children and senior citizens in rural and urban homes are selected for study, some residents with more exposure patterns are not included (e.g., residents with high occupational exposure). Third, it is necessary to obtain point-to-point respiratory volume (respiratory rate) data when measuring real-time $PM_{2.5}$ exposure data and incorporate respiratory volume (respiratory rate) into the analysis of $PM_{2.5}$ exposure. Finally, although the questionnaires were finished by trained graduate students, it's challenging to recall the time spent in each microenvironment without any uncertainty. In the future, AI technologies may be adopted in exposure science with the synchronized information of exposure concentration and time-activity. It's welcomed that more studies pay attention to environmental inequity in the near future using the novel method adopted in this study.

4 Conclusion

In this study, field measurement was conducted to explore the real-time $PM_{2.5}$ exposure of urban and rural residents in Mianyang City, Sichuan Province. The contributions of different activities to $PM_{2.5}$ exposures and $PM_{2.5}$ exposure inequity between rural and urban residents were further discussed. Results showed that the $PM_{2.5}$ exposure levels varied largely among different resident groups, with higher $PM_{2.5}$ exposure of rural residents than those of urban residents. Real-time $PM_{2.5}$ exposure showed that $PM_{2.5}$ exposure peaks mostly occurred in (Aaccompanied) cooking owing to strong internal emissions. Sleeping and resting contribute 60.7%–94.5% to $PM_{2.5}$ exposures. (Accompanied) cooking had the highest exposure concentration among different activities. Exposure inequity between urban and rural areas is dominated by pollution variation in different microenvironments, which is associated with the socio-economic, behavioral, or environmental factors. For instance, households with higher incomes tend to use cleaner fuels compared to those with low incomes, resulting in lower indoor air pollution, and lower exposure levels (Lim et al. 2022). Moreover, urban areas suffer from higher ambient air pollution due to industrial emissions, people in rural areas benefit from better ambient air quality because of limited anthropogenic source emissions (Wang et al. 2022). Rural residents face a higher risk from $PM_{2.5}$ exposure, with a significant contribution from indoor air pollution. Therefore, accelerating the transition to clean energy in rural areas can help reduce the exposure of rural residents. Improved ventilation in rural homes is necessary, and measures such as adopting range hoods and air purifiers are encouraged (Huang et al. 2022; Oh et al. 2024). For urban residents, they can benefit from better ambient air quality by promoting the reduction of industrial and transportation emissions. Moreover, the government should raise public awareness of indoor air pollution, which will help the public take measures to reduce indoor emissions.

The contributions of different activity patterns to $PM_{2.5}$ exposure inequity also varied largely among different resident groups. Among these factors, pollutant concentrations in certain microenvironments and the duration of activities were the main reasons for exposure inequity. The combustion of solid fuel leads to higher air pollution in bedrooms of rural homes, and the long duration of sleeping makes it the predominant activity contributing to $PM_{2.5}$ exposure inequity. In addition, the contribution of different activity patterns to $PM_{2.5}$ exposure inequity varied significantly when respiratory volume was considered. This study aimed to build a new method to quantify the contribution of activity patterns to $PM_{2.5}$ exposure inequity between urban and rural residents, utilizing real-time $PM_{2.5}$ data and time-activity information. However, the study was conducted only during a summer campaign. Due to variations in meteorological conditions, residential fuel choices, and emissions from other sources, the results may differ in other seasons. In the future, more studies are welcomed to focus on this topic to better address the exposure inequity and its underlying drivers.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

All authors contributed to the study conception and design. Investigation was performed by Tao Jiang, Yungui Li and Yuqiong Wang. Formal analysis was performed by Tao Jiang, Yungui Li, Yuqiong Wang and Zhanpeng Cui. Data curation was performed by Zhanpeng Cui, Jinze Wang and Wei Du. The first draft of the manuscript was written by Wei Du and Zhanpeng Cui and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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