



Study of the Characteristics and Comprehensive Fuzzy Assessment of Indoor Air Chemical Contamination in Public Buildings

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Quality-of-life is improving daily with continuous improvements in urban modernization, which necessitates more stringent requirements for indoor air quality. Fuzzy assessment enables us to obtain the grade of the evaluation object by compound calculation with the help of membership function and weight coefficient, overcoming the limitations of traditional methods applied to develop environmental quality indices. First, this study continuously measured SO₂, O₃, NO₂, NO, CO, CO₂, PM₁₀, PM_{2.5}, and other chemical pollutants during the daytime operating hours of a library and a canteen. We analyzed the concentration distributions of the particles in the air were discussed based on 31 different particle diameters. Finally, the experimental data in department store and waiting hall were analyzed by fuzzy evaluation, with the following results. (1) The library and canteen PM_{10} concentrations peaked at 07:45 in the morning and was elevated during the afternoon (48.9 and 59 μ g/m³, respectively). (2) The Pearson correlation coefficient of the PM_{10} and $PM_{2.5}$ concentrations in the library was 0.98. PM_{10} and SO_2 in the canteen were negatively correlated, with a correlation coefficient of -0.65. PM_{2.5} and PM₁ were always highly positively correlated. (3) The high concentration of particles in the library was associated with the small particle size range $(0.25 \sim 0.45 \,\mu\text{m})$. (4) By applying the fuzzy comprehensive evaluation method, the library grade evaluation was the highest level, and the waiting hall was the lowest. This study enhances our understanding of the indoor chemical contamination relationships for public buildings and highlights the urgent need for improving indoor air quality.

Keywords: fuzzy assessment, indoor pollutant concentration, air quality, correlation analysis, $PM_{2.5}$

INTRODUCTION

Indoor air pollution has become a hot topic because we realize that outdoor pollutants may infiltrate into indoor places and that these indoor areas may also have various sources of pollutants. An increasing number of people believe that indoor air pollution has an equal or even greater significant impact on human health compared with that of atmospheric environmental air quality (1). Depending on the geographic area, age, sex, work activities, and season, people spend $\sim 87.5\%$ of their day indoors (2). The number of German children spending a majority of their day indoors is $\sim 75\%$ (3), while the corresponding percentage of American adults is over 90% (4). Particulate matter concentrations and some indoor parameters may be only a fraction of those of outdoor

OPEN ACCESS

Edited by:

Efstratios Vogiannis, National Observatory of Athens, Greece

Reviewed by:

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Specialty section:

This article was submitted to Environmental health and Exposome, a section of the journal Frontiers in Public Health

> **Received:** 02 July 2020 **Accepted:** 29 March 2021 **Published:** 05 May 2021

Citation:

Liang X, Li Z, Zhang H and Hong X (2021) Study of the Characteristics and Comprehensive Fuzzy Assessment of Indoor Air Chemical Contamination in Public Buildings. Front. Public Health 9:579299. doi: 10.3389/fpubh.2021.579299

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pollutants, but this generally occurs only when there is no indoor source. When there is an indoor source, the indoor concentration of pollutants can exceed the outdoor concentration (5, 6). With the increasing frequency of hazy weather and the increasing degree of pollution, the issue of chemical pollutants has become increasingly prominent.

Differences in the airtightness of buildings may lead to significantly higher indoor concentrations of pollutants than outdoor concentrations, which may also be due to the full range of indoor emission sources (7). Indoor air quality presents one of the significant environmental risks to human health (8, 9). Studies have shown that exposure to indoor air pollutants can have a wide range of health effects. Ozone is an air pollutant with a multitude of potential adverse health effects. Hu et al. (10) found that indoor oxidizing gaseous pollutants, i.e., O₃, had potential physical and chemical damage to objects indoors; moreover, ozone can also induce respiratory inflammation in healthy people and people with respiratory diseases such as asthma (11). Ozone is also associated with increased hospital admissions (12). Huang et al. suggested that indoor ozone <10ppb was associated with cardiovascular responses in children (13). The impact of indoor exposure to particulate matter on health depends on the particle size, with particle sizes $<1 \,\mu m$ having the greatest impact (14). PM2.5, PM10, and NO2 were found to increase wheezing and rhinitis symptoms among preschool children in China (15), and Asian schools presented higher levels of PM and PAHs than did European and American schools (16). Kidney damage induced by subchronic fine particulate matter exposure, especially exposure to PM2.5, may induce fibrosis and mesangial expansion (17). Children displayed significant associations between PM exposure and asthma, and in adults, PM2.5 was associated with asthma, bronchitis, and combined respiratory problems (18). In general, there is an association between children's health and exposure to ultrafine particles (UFPs), especially among children with respiratory diseases, who commonly experience alterations in inflammatory biomarkers and deterioration in lung function as a result of UFP exposure (19). Formaldehyde, which is a ubiquitous organic pollutant often found indoors, has recently been identified as a human carcinogen (20, 21). Long-term exposure to $PM_{2.5}$ has been associated with an increased risk of new-onset depressive symptoms, while increased concentrations of nitric dioxide during summer are associated with the worsening of existing depressive conditions (22, 23). Exposure to low concentrations of NO_2 increases the risk of premenopausal breast cancer (24–26), and we found evidence that long-term exposure to particulate matter and NO₂ were linked with the development of heart failure (27). SO₂ can change testicular structures and increase sperm malformation (28, 29). Volatile Organic Compounds (VOCs) are widely reported in public buildings. The World Health Organization, the Committee on Indoor Air Pollution Japan, the US Environmental Protection Agency and Public Health England have assessed the evidence and listed the potential health effects of VOCs, including irritation of the eyes and respiratory tract, allergies and asthma, central nervous system symptoms, liver and kidney damage, as well as cancer risks (30, 31). Therefore, a variety of pollutants, not only those causing discomfort, should be considered when assessing indoor air quality.

However, there is currently a lack of comprehensive indicators for use in indoor air quality assessment. We aim to apply an indoor air quality assessment program based on fuzzy analysis to improve on previous methods of indoor air quality assessment. Many scholars have studied indoor air quality assessment methods, and their mathematical models were formed using a variety of methods, such as objective and subjective evaluations, as well as integrated and unified assessments. Some scholars have studied the decipol evaluation method and air quality index method (32, 33), but the methods could not quantitatively express the perceived air quality or dynamically track pollutants, respectively. The indoor air pollutant gray clustering model is proposed to simplify the evaluation of indoor air quality, but it is impossible to adjust the critical evaluation criteria sequence (34). Office buildings in Brisbane, the capital city of Queensland, Australia, have no obvious pollution indoors, yet there is a strong correlation between particle concentrations of indoor and outdoor pollutants there (35). Formaldehyde and toluene are major indoor pollutants of concern in newly constructed apartment buildings (36). However, research on these pollutants does not consider the chemical pollutant effect on the relationship between indoor and outdoor concentrations of PM_{2.5}. In addition, these studies lack high-time resolution monitoring data, so there is still room for improvement.

This article is based on a study of a library and canteen in two public buildings in Guangzhou, China, where the indoor chemical pollutant concentrations were measured with the windows closed and with the windows open for ventilation in the spring. We analyzed the air quality according to the indoor and outdoor PM_{2.5} and PM₁₀ concentrations and the changing trend of each pollutant and calculated the correlation between the chemical pollutants, as well as the particle size distribution of the indoor particulate matter. Statistics are presented for the concentrations corresponding to three main occupational health concerns from indoor pollutants, including Inhalable, Thoracic, and Alveoli categories. Additionally, the experimental data in department store and waiting hall were analyzed by fuzzy evaluation. These studies on the effects of indoor and outdoor PM_{2.5} levels provide a basis and method for reference, as well as a reference for long-term health assessments for practitioners in the area.

MATERIALS AND METHODS

Sampling Sites and Time

We selected a library ($113.4019^{\circ}E$, $23.0439^{\circ}N$), a canteen ($113.3904^{\circ}E$, $23.0485^{\circ}N$), a waiting hall ($113.3502^{\circ}E$, $23.1761^{\circ}N$), and a department store ($113.3983^{\circ}E$, $23.0688^{\circ}N$) in China as the test objects. The library, the canteen, and the department store are located on the campus of a university in Panyu district of Guangzhou. The waiting hall, located in Tianhe District, is intended as a terminal station for a number of bus passengers. The field experiment was conducted for a total of 4 days, on April 15, 16, 24, and 25, 2019. In the first-two-day experiment, the test duration for each kind of ventilation was

 \sim 8 h in the daytime after opening. The specific timetable of the field experiment is shown in **Table 1**. It is worth mentioning that in the last two measurements of April 24 and 25, to verify the fuzzy assessment, we focused on the peak hours of public buildings. Therefore, the concentration it measured will only be used to carry out feasibility analysis of the fuzzy comprehensive evaluation model.

The indoor and outdoor $PM_{2.5}$ and other pollutants were measured in the centralized central air conditioning. During the test period, there were no distinct outdoor $PM_{2.5}$ or other pollution sources, such as construction projects, rain or hazy weather. The information about sampling sites is listed in **Table 1**. The internal and external windows of the test area were closed throughout the whole process, and the indoor area was equipped with a VRF system. Data from each site was dynamically recorded by testers. All indoor rooms were nonsmoking rooms.

Sampling Method

According to the relevant provisions of the indoor air quality standard (UB/T 18883-2002), the sampling points for monitoring the concentrations of chemical pollutants in the library were arranged on a desk table on the 4th floor (8 floors in total), 4.3 m away from the exterior window of the building and 1.0 m high. The sampling points for measurements of the canteen were arranged in the customer dining area on the first floor and close to the outer pane of the canteen. The measuring point was 1.0 m from the ground and 3.2 m from the external window. The specific layout is shown in **Figures 1**, **2**. We also chose the central location of the other two buildings as the measuring point.

Sampling Instrument

The mass concentrations of indoor particles were recorded by a portable laser aerosol diameter spectrometer (11-R, GRIMM Aerosol Technique Airing Inc., Germany) at an interval of 1 min in real time. After the test, the measured data were uploaded to the connected workstation computer via a serial port to a USB data line. SO₂, O₃, NO₂, NO, and CO were recorded by the air quality monitoring system (HIM-6000, Haz-Scanner Inc., U.S.A) at an interval of 5 min. A portable infrared component gas analyzer (Gasboard-3100P, Cubic-Ruiyi Inc., China) assessed CO₂ and CH₄ at an interval range of 5 min in real time. The hourly outdoor pollutant data were monitored in real time by the nearest Chisha monitoring station. The data were obtained from the real-time air quality release system issued by the Guangzhou Environmental Monitoring Center station, and we obtained the changes in pollutant concentrations at each monitoring point through a summary of statistics. The measurement ranges and accuracies are listed in **Table 2**.

Instrument Calibration

Compared with standard equipment, the measurement data of the portable sensor often has some linear error. Therefore, the portable sensor needs to be measured in the same place for a long time with standard equipment. Finally, the measurement results of the portable device are compared with the measurement results of standard equipment. In relation to data quality control, all the portable monitors were first calibrated before leaving the factory, and further estimations were made using standard methods prior to this study. Data calibration was first conducted at the Guangdong University of Technology (GDUT) on April 9, 2019. Calibration checks since then have been routinely performed before and after each run.

Processing Measurement Data Rejection of Outliers

Some sudden human activities (such as vehicles operating or suddenly starting near the testing area) often lead to abnormally high values of pollutant samples in dining areas or reading rooms (1, 37, 38), which may distort real pollution trends or aggravate typical-source pollution levels. The performance of the running coefficient of variation method was more convincing than those of other methods, making it an excellent choice for outlier sample testing and for elimination in air quality detection (39, 40). With this study's primary focus on indoor air pollution trend analysis to characterize general air quality trends. Theoretically, isolation of indoor air pollution trends may be simplified by site selection in an outdoor environment where roadways surrounding have no external human interference. However, such ideal conditions are rare and often studies need to consider these random events. Therefore, the pollutant indicators closely related to temporary anthropogenic emissions and the more sensitive pollutants needed to be determined. PM25 was selected as the reference in this paper. Next, based on the particle sample sequence of 1-min resolution, the 5-min slip variation coefficient of single-sample data was calculated. The calculation formula is as follows:

$$RCOV_{s} = \frac{\sqrt{\frac{1}{5}\sum_{i=s-2}^{i=s+2} (a_{i} - \overline{a})^{2}}}{\overline{a}_{all}}$$
(1)

where $RCOV_s$ is the 5 min running variation coefficient of the *s*th measured PM_{2.5} data; a_i is the *i*th measured PM_{2.5} data; \overline{a} is the mean value of the *s*th measured PM_{2.5} data and the two adjacent

TABLE 1 | The timetable of the field experiment.

Site	Time	Ventilation	Area
Library	08:00~16:30	Mechanical	112.60 m ²
Canteen	07:00~16:00		101.25 m ²
Waiting hall	11:30~12:30		150.00 m ²
Department store	11:30~12:30		162.50 m ²
	Site Library Canteen Waiting hall Department store	Site Time Library 08:00~16:30 Canteen 07:00~16:00 Waiting hall 11:30~12:30 Department store 11:30~12:30	SiteTimeVentilationLibrary08:00~16:30MechanicalCanteen07:00~16:00Vaiting hallWaiting hall11:30~12:30LibraryDepartment store11:30~12:30Library



samples collected before and after; and \bar{a}_{all} is the mean value of all measured PM_{2.5} data in a one-day experiment. The 99th quantile of the 5-min sliding coefficient of variation of all PM_{2.5} data was taken as the threshold, and measured PM_{2.5} data larger than this threshold were regarded as data of abnormally high values and were eliminated along with the two adjacent PM_{2.5} data collected before and after.

Taking PM_{2.5} as an example, the library involved a continuous daytime measurement lasting ~8 hours (the total number of samples with 1-min resolution was 526). In each experiment, samples with abnormally high values identified by the *RCOV* (the 99th quantile was ~0.1269) method accounted for 0.56% of the total samples at 08:14~08:16. By combining these data with the outdoor data (**Figure A1**), we observed that the particle mass concentration at the monitoring site of Chisha also fluctuated slightly at this time. The test day was a working day, and the east wind prevailed during the season. The library was located on the southwestern side of a specific intersection, which experienced frequent working conditions of motor vehicles during the morning rush hour when teachers,



FIGURE 2 | Field layout of the indoor measuring instruments. Data from both sites were dynamically recorded by testers.

students and staff of the school commuted to work. Such temporary and complex peripheral environmental factors were often accompanied by abnormally high-value $PM_{2.5}$ samples during the measurement process.

Dynamic Correction

In general, dynamic testing experiments with specific functions or polynomial fitting may be used to process data if certain and uncertain factors need to be distinguished. However, sometimes, it is difficult to know the functional form of measured and complex test data, or it is difficult to know which polynomial to choose. Occasionally, we need to eliminate the random fluctuation in dynamic test data. It is not necessary to express its change rule in the form of some function or as the sum of some features, but it is necessary to reveal its definite change rule according to the value of the point function (41–44). It is also tricky to directly compare and process data from instruments with different time resolutions, so dynamic correction is required.

Based on previous studies, a relatively ideal correction method based on a time series, a 5-point equal-weight smooth-thin plate spline regression method (5S-TPS), was proposed, and the measured data from two the locations were used in the data processing (39, 42). This method was divided into three steps. (1) Along the full length of N data, the original pollution samples with the resolution of 1 min were processed with a 5-min moving average. Thus, five adjacent data points were continuously measured one by one to determine the arithmetic average. (2) The moving average results were divided into equal parts according to the specified time window (such as 5 min), and the positions of the specific time nodes of pollutant concentrations were identified in each corresponding window to eliminate random errors and synthesize time resolutions matching those of the other instruments. (3) Thin-plate spline regression was used to conduct smoothing fitting for the sample of the sliding mean value of the pollutant concentration at the specified time node obtained in the previous step.

Correlation Analysis

After the dynamic correction described above, the data with a time resolution of 1 min were compared with the data with a resolution of 5 min at the same time-scale interval. Here,

Contamination	Instrument model	Range	Accuracy	Resolution	Manufacturer	Producing area
SO ₂	HIM-6000	0~5000 ppb	±5 ppb	5 min	Haz-Scanner	U.S.A.
NO ₂	HIM-6000	0~5000 ppb	±5 ppb	5 min	Haz-Scanner	U.S.A.
NO	HIM-6000	0~25 ppm	$\pm 10 \text{ ppb}$	5 min	Haz-Scanner	U.S.A.
СО	HIM-6000	0~100 ppm	±0.01 ppm	5 min	Haz-Scanner	U.S.A.
CO ₂	Gasboard-3100P	0~40%	$\pm 1\% FP$	5 min	Cubic-Ruiyi	China
CH ₄	Gasboard-3100P	0~75%	±1%FP	5 min	Cubic-Ruiyi	China
O ₃	HIM-6000	0~150 ppb	± 0.1 ppm	5 min	Haz-Scanner	U.S.A.
PM _{2.5}	11-R	$0.1~\mu\text{g/m}^3 \sim 100~\text{mg/m}^3$	±3%	1 min	GRIMM	Germany
PM ₁₀	11-R	$0.1~\mu\text{g/m}^3 \sim 100~\text{mg/m}^3$	±3%	1 min	GRIMM	Germany
PM ₁	11-R	$0.1~\mu\text{g/m}^3 \sim 100~\text{mg/m}^3$	±3%	1 min	GRIMM	Germany

TABLE 2 | The measurement ranges and accuracies.

the Pearson correlation coefficient R_p was used to judge the correlation between the pairwise measured parameters of each chemical pollutant. The calculation formula is as follows:

$$R_{\rm p} = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$
(2)

where x_i and y_i (i = 1, 2, 3...) are the sample values and \bar{x} and \bar{y} are the sample mean values. The value range of the correlation coefficient is $|R_p| \le 1$, and the closer the absolute value is to 1, the greater is the correlation between variables x and y. Generally, $|R_p| > 0.8$ means highly correlated, and $|R_p| < 0.3$ means weakly correlated. This portion is implemented using the R programming language operation platform RStudio.

Description of Fuzzy Evaluation

Fuzzy Comprehensive Evaluation is a famous method and has extensively been applied in many fields including wind farm investments, masonry structure safety, teaching performance, and landslide susceptibility (45–48). It is able to help the researchers to find out the most important factors that should be prioritized by using mathematics. It has been proved that the combined application of fuzzy mathematical method on the air assessment is not only objective but also quantitative (49). A fuzzy inference system is quite appropriate for subjective issues like environmental conditions, because it can appropriately classify them (especially in the case of boundary levels that are failed to be sensitively classified by conventional methods), help a balance between different and sometimes contradictory observations be achieved, and finally help subjective and non-quantitative issues like air quality assessment be well-classified and quantified (50).

The discontinuous distribution of the air pollution grading index concentration was inconsistent with the continuous distribution of the indoor air quality index. Given the inherent complexity, risks and uncertainties of AQI and the diversity of sites, this paper aims to introduce a novel assessment framework for contamination using fuzzy assessment as a recent approach dealing with uncertainties in in the field of indoor air quality evaluation. Introducing the fuzzy mathematics principle to this study of the public space involved using monitoring data to create the corresponding fuzzy mathematical model. The model was applied to six evaluation objects for the indoor environmental air quality. The fuzzy comprehensive evaluation was based on monitoring of the indoor air pollution, and personnel from these public workplace buildings were provided with the health assessment to provide a scientific basis for breathing. The prevalence of sick building syndrome has caused people to focus increasing attention on the problem of indoor air quality. Therefore, among the many methods of indoor air quality evaluation, the fuzzy mathematics theory is a highly recognized method (51–53).

The specific evaluation steps (Figure 3) were as follows:

1) Determine the evaluation standard set of the research object $V = \{V_1, V_2, ..., V_m\}$ according to the improved indoor evaluation

index (54), and combine the set with the actual situation of the indoor air pollution, with each degree factor of environmental air pollution divided into five levels, namely, I (clean), II (light pollution), III (moderate pollution), IV (heavier pollution), and V (polluted).

2) Determine the evaluation factor set of the research object $U=\{U_1, U_2, ..., U_n\}$. According to a comprehensive analysis of various indicators affecting the environmental air quality (52, 55), primary pollutants in the air include the following six items: PM_{2.5}, PM₁₀, CO, O₃, SO₂, and NO₂. Therefore, the established evaluation factor set is $U=\{PM_{2.5}, PM_{10}, CO, O_3, SO_2, NO_2\}$.

3) Determine the factor weight set. We studied the medical literature and rearranged the weight coefficients of pollution parameters affecting the indoor air quality according to the degree of influence of various air chemical pollutants on human health (49). They were PM_{2.5}(0.25), PM₁₀(0.2), CO(0.2), O₃(0.15), SO₂(0.1), and NO₂(0.1); thus, the factor weight set is $A=[a_1, a_2, ..., a_5]=[0.25, 0.2, 0.2, 0.15, 0.1, 0.1].$

4) Establish membership functions. A membership function is a curve with different possible shapes (for example, trapezoidal, triangular, or gaussian) that shows how each point in the input space is related to membership value between 0 and 1 (50). According to the above evaluation factor set and evaluation standard set, combined with the actual situation of the research problem, this paper established the membership function r_{ij} of each pollution factor for each level standard in the form of a reduced half trapezoid function, and the specific calculation formula is as follows:

For level I, i.e., j = 1, the membership function expression is:

$$r_{1i} = \begin{cases} 1, u_i \leqslant s_1 \\ \frac{s_2 - u_i}{s_2 - s_1}, s_1 < u_i < s_2 \\ 0, u_i \geqslant s_2 \end{cases}$$
(3)

For level II - IV, i.e., j = 2, ..., m-1, the membership function expression is:

$$r_{ji} = \begin{cases} 0, u_i \leq s_{j-1} \\ \frac{u_i - s_{j-1}}{s_j - s_{j-1}}, s_{j-1} < u_i < s_j \\ \frac{s_{j+1} - u_i}{s_{j+1} - s_j}, s_j < u_i < s_{j+1} \\ 0, u_i \geq s_{j+1} \end{cases} (j = 2, \dots, m-1)$$
(4)

For level IV, i.e., j = m = 5, the membership function expression is:

$$r_{jm} = \begin{cases} 0, u_i \leqslant s_{m-1} \\ \frac{u_i - s_{m-1}}{s_m - s_{m-1}}, s_{m-1} < u_i < s_m, m = 5 \\ 1, u_i \geqslant s_m \end{cases}$$
(5)

In the above piecewise expression of the function, *i* represents an evaluation factor in the evaluation factor set U; *j* represents an evaluation standard in the evaluation standard set V; u_i represents the measured pollutant concentration value at a particular place of the *i*th evaluation factor; and s_j represents the concentration limit of the *j*th grade of the *i*th evaluation factor.

5) Establish the fuzzy comprehensive evaluation matrix. The monitoring values of the pollutants were substituted into



the corresponding membership function expression, and the membership degree of each evaluation factor to each grade was calculated, forming the membership degree set of each pollution factor. Namely, the single-factor evaluation of the *V* i factor $R_i = (r_{i1}, r_{i2}..., r_{in})^T$ was a fuzzy subset, in which r_{in} represents the membership degree of the *i*th factor for the *j* grade, and the evaluation matrix of all factors is $R = (R_1 R_2... R_n)$.

6) Compound the membership matrix R, which is obtained above, and the weight matrix A to obtain the comprehensive evaluation vector B, that is, $B = A \cdot R = (b_1, ..., b_m)$. In traditional fuzzy mathematical theory, b_k is assumed to be b_j (j = 1) according to the maximum membership principle, and it can be concluded that the indoor air quality belongs to grade k.

$$B = [a_1 \ a_2 \dots a_m] \begin{bmatrix} r_{11} \ r_{12} \ \dots \ r_{1n} \\ r_{21} \ r_{22} \ \dots \ r_{2n} \\ \dots \ \dots \ \dots \\ r_{m1} \ r_{m2} \ \dots \ r_{mn} \end{bmatrix} = (b_1 \ b_2 \dots b_n) \quad (6)$$

RESULTS AND DISCUSSION

Overall Characteristics of Each Pollutant During the Measured Period

Guangzhou is located in the region with a hot summer and warm winter, one of the five climate zones of China. During

the spring measurements, the weather was clear, and there was no cloudy rain or haze. According to the ambient air quality standard (GB 3095-2012), during the test, PM2.5 concentrations of 35 μ g/m³ and PM₁₀ concentrations of 50 μ g/m³ could be used as the particulate level A judgment standard. For the library, the indoor air concentrations of PM2 5 and PM10 could achieve level A standards. Most of the time, before 08:15, the distribution of PM_{2.5} concentrations was at level B, and during the afternoon session (14:00 to 15:00), the indoor PM₁₀ concentrations were at level B, while the outdoor PM₁₀ concentrations were at level A. It can be seen from Figure 4 that there was an apparent synchronism between the indoor particulate matter and outdoor particulate matter in the library. PM2.5 and PM10 both showed a trend of first decreasing, then increasing and finally decreasing during the test. Surprisingly, the timing of the peak of the particulate matter was inconsistent. Taking PM₁₀ as an example, the peak value in the library was at \sim 07:45 in the morning (48.9 μ g/m³), while the peak value in the library was at ~14:00 $(59 \ \mu g/m^3)$ in the afternoon. When the public building was open, positive pressure formed in the room. Furthermore, the air conditioner was turned on. Thus, the permeability of particles leads to a difference in concentration between the inside and outside areas. The overall outdoor PM2.5 level did not change much, but the indoor PM2.5 concentration was higher than the outdoor concentration during the period from 9:00 to 13:00.

Most of the time, the concentrations of PM_{2.5} and PM₁₀ in the air of the canteen could reach standard level A, with PM_{2.5} concentrations at level A in the daytime, while at noon (12:00-12:30), the indoor PM₁₀ concentration could reach level B (Figure 4). The pollution from cooking combustion sources had certain relevance to these data. Unlike the library, the canteen showed inconsistent indoor and outdoor particulates due to the existence of internal pollution sources. The changing trends of indoor PM2.5 and PM1 were the same, but the concentration of PM₁₀ changed sharply and was higher than the outdoor value at many times. PM1 concentrations peaked at ~07:19 am (28.5 μ g/m³) in the canteen, PM_{2.5} concentrations peaked at ~07:17 am (32.8 μ g/m³), and PM₁₀ concentrations peaked at ~16:11 P.M. (56.7 μ g/m³). The PM_{2.5} concentration in the canteen reached extreme values during the cooking periods before breakfast, lunch and dinner, with concentrations of 32.5, 30.6, and 30.3 μ g/m³, respectively. Cooking oil fumes contain massive particulate matter according to Du et al. (56), which can escalate the concentrations at meal times.

The primary indoor and outdoor chemical pollutants were inconsistent. The main indoor pollutant was particulate matter, while the primary outdoor pollutant was CO. NO in the library fluctuated sharply within the range of $0\sim10$ ppb, while SO₂, O₃ and NO₂ were below 14 ppb. Taking 09:00 am as an example, the I/O ratio of CO was 1.25, the I/O ratio of NO₂ was 0.11, the I/O ratio of O₃ was 1.43, and the I/O ratio of SO₂ was 1.07 (**Figure A2**). These amounts were still higher than the outdoor concentrations, although the indoor chemical pollutants did not exceed the standard limits.

Figure A3 and **Figure A4** in appendix show the hourly variations in the percentages of 6 gases in the two locations. The variation trend of CO produced values that remained almost the



same, but the concentration of CO_2 gradually accumulated in the library, which may have been related to the building tightness and the increase in personnel. CO_2 in canteen reached two peaks during the morning. At noon, the bulk concentration exceeded the daily value of 0.03% at most moments, and the maximum value reached 0.19% at 13:38 at noon. The volume concentration of CH₄ was always below 0.3%, the volume concentration of C_nH_m was almost 0%, and the difference between H₂ and O₂ was not significant.

Effects of Indoor Air Chemical Pollutants

According to the above analysis, the trends of different pollutants in different indoor environments were different. To further explore the relationships between the pollutants, the Pearson correlation coefficient R_p was used to judge the correlation between the pairings of the measured parameters. The results are shown in Figure 5. The main diagonal shows the categories of pollutants listed, and the size of the circle in the upper right indicates the correlation between the two pollutants. The larger is the graph, the stronger is the relationship; the darker is the blue color, the stronger is the positive correlation; and the darker is the red color, the stronger is the negative correlation. The value in the lower-left region is the Pearson correlation coefficient between the pairings, and the color depth also corresponds to the graphic meaning. In the library, PM10, PM2.5, and PM1 had a strong positive correlation (the correlation between PM₁₀ and PM2.5 reached 0.98; 0.99 was for PM2.5 and PM1; and 0.96 was for PM₁₀ and PM₁). SO₂ showed a weak negative correlation with particulate matter, with correlation coefficients of $-0.23(PM_{10})$, $-0.26(PM_{2.5})$, and $-0.28(PM_1)$. In the canteen, O₃ and NO₂ had the strongest positive correlation, with a coefficient of 0.96. The correlation coefficient between PM2.5 and PM1 was 0.92. Due to the existence of internal pollution sources, the concentration of PM₁₀ was relatively high and not synchronized with those of other particles, and its correlation coefficient with PM1 was only 0.02. At this time, PM₁₀ and SO₂ were negatively correlated with each other, and the correlation coefficient was ~ -0.65 . PM₁ and O₃ also had a highly negative correlation, with a value of -0.69. Although the Pearson correlation coefficients of the same chemical pollutants in different public buildings varied greatly, PM_{2.5} and PM₁ were always highly positively correlated, O₃ in the library was weakly positively associated with other pollutants, and PM_{2.5} in the canteen was almost negatively correlated with other contaminants, and PM1 has the same characteristics.

Distribution of Indoor Air Particles

For the two locations, statistical tests were performed for the three kinds of particle size distributions in the mass concentrations of the particulate matter (Figure 6). Different concentrations of the object operation platform were tested, and using the R programming language RStudio (Version 1.2.1335) and an integrated development environment, a summary was plotted as a violin plot. The violin plot combined the boxplot and density figure characteristics to avoid hiding important details about the data distribution and could reflect the dispersion density and distribution of each interval period. The outer shape of the filled color block in the figure is the kernel density estimation, which was used to estimate the unknown density function in the probability theory. In one set of tests, the more times the concentration of a certain x-coordinate appeared, the larger was the y-coordinate value of the reaction on the graph, and the more concentrated was the whole graph. The data of the 95% sample values could be statistically analyzed in the violin plot using the R programming language. The results showed that the plot of the concentrations of particulate matter in the library was gourd-shaped, and the data in the middle and bottom areas were relatively concentrated. Among them, the highest concentrations of PM_{10} were 26.5 μ g/m³ and 16.6 μ g/m³, with each accounting for 1.68% of the total data. The mass concentrations of $PM_{2.5}$ were 24.0 μ g/m³, accounting for 2.34%, and 16.2 µg/m³, accounting for 1.49%. PM₁ accounted



for 2.98% and was present at 22.3 μ g/m³. The distributions of the three particles were similar. The mass concentrations of particulate matter in the canteen were distributed in a spindle shape. The mass concentrations of PM₁₀ were the most dispersed, and those of PM_{2.5} and PM₁ were both concentrated. The most frequent concentration was 38.7 μ g/m³, accounting for ~1.85%. The PM_{2.5} concentration of 24.3 μ g/m³ was as high as 4.07%. The PM₁ concentrations were 21.0 μ g/m³ and 19.2 μ g/m³, which accounted for 3.14%. In the canteen, the larger the particle size, the higher was the concentration.

In this study, we calculated the particle distributions of particles with different single particle sizes on the same day, and a particle diameter-time-concentration distribution map (DTC map) was drawn so that the distributions of the various parameters could be more intuitively examined. As shown in Figure 7, a small number of particles with diameters above 17.5 μ m had a concentration of more than 10 μ g/m³, while the particles with different particle sizes were mainly concentrated below 4 μ g/m³. The particles measured at the 95% sample values in the library and canteen were analyzed as shown in Figure 8. The particle sizes below 6.5 µm in the library changed obviously, and the particle sizes above $6.5\,\mu m$ were 0 or occasionally slightly fluctuated. Particles with particle sizes below $0.45 \,\mu$ m first decreased and then increased in the morning, and the curve changed significantly. The mass concentration of particles with particle sizes of 0.5~1.30 µm was relatively stable, ranging from 0.55 to 0.79 μ g/m³. The concentration of particles with particle sizes of $1.6 \sim 5.0 \,\mu\text{m}$ changed significantly, with a range of $0.03 \sim 3.34 \ \mu g/m^3$. The general trend also indicated a first decrease and then an increase over time during 1 day. The concentration of particle sizes from 6.5 to 32.0 µm was occasionally prominent but almost maintained at 0 μ g/m³ throughout the day. In the canteen, the particle

concentration of 0.25~0.58 µm particle sizes was lower than 3.48 μ g/m³, and the concentration of 0.65–0.8 μ m particle sizes was 0.17 μ g/m³. Different from the case for the library, the particle sizes were within the range of $15 \sim 32.0 \,\mu$ m, so the concentrations were almost maintained at $0 \ \mu g/m^3$ all day. By comparing Figures 8C,D, it is not difficult to find that the high concentrations of particles in the library were localized within the small particle size range $(0.25 \sim 0.45 \,\mu\text{m})$, while the high concentrations of particles in the canteen were in the medium particle size range of 2.0~8.5 µm. The mass concentrations of large particulate matter (>15 μ m) in both places were close to zero. Figures 8E,F show the time distributions of particulate matter in a day. The concentration distribution in the library was relatively regular, with a significant peak and valley period, which is consistent with the variation trend in the outdoor particulate matter concentration. The particles in the canteen were relatively dispersed during the day, and there were no periods when the particle size was too concentrated.

Workplace Health Assessment of Airborne Particulate Matter in Public Buildings

Promulgated by the BS EN 481 standard of the British Standards Institution, air particles in the atmosphere of the workplace affect safety accordingly. Particles in the size range of 10–100 μ m were considered to be inhalable particulate matter (Inhalable fraction). Those particles with sizes between 4 and 10 μ m were considered to be inhalable thoracic particulate matter (Thoracic sub fraction), and particles of other sizes <4 μ m belonged to alveoli particulate matter (Alveoli fraction) (57).





In this test, the particle size mass concentrations of two public buildings were classified and statistically calculated. There were significant differences in the concentration of different types of particulate matter in different public buildings (p < 0.01,

Friedman test). A box plot was added based on the violin plot to highlight the value distribution, and the result is shown in **Figure 9**. The gray box on the line in the middle of the fill block represents the quartile range, the fine gray



line extending from it represents the 95% sample values, and the thick gray line in the center of each box represents the median. The x-coordinate is the particle classification, and the y-coordinate is the particle mass concentration. As shown in **Figure 9**, the canteen had the most concentrated inhalable alveoli particles, with a median mass concentration of 27.6 μ g/m³ and an overall concentration of 26.3 \sim 28.8 μ g/m³. The inhalable particulate matter mass concentration of the dispersed (median



41.2 μ g/m³) and inhalable particle concentration after the inhalable thorax particulate matter pulmonary alveolus ranged between 33 and 40.03 μ g/m³. In the library, the three kinds of workplace air-particulate-mass-concentration distributions were similar. As seen from the figure, the concentrations of particles in the library fell at both ends, and the mass concentrations of human-inhalable particles were ~16.7 and 30.7 μ g/m³. Upon comparing the particulate matter at the two sites, the mass concentration of inhalable particulate matter in the canteen was found to be 1.52 times higher than that in the library.

The mass concentrations of particulate matter were plotted based on the time duration. As shown in Figure 10, the canteen experienced a peak in inhalable particulate matter concentrations of 209.8 μ g/m³. At the specific time of 12:02, the pollution situation in the workplace was more serious because this point was during lunch time, and the cooking sources of particulate matter were more complicated. The mass concentration of either particle was higher than 20 μ g per m³. Considering the BS EN 481 standard, the concentrations of particulate matter during business hours were maintained at relatively high levels. The three workplaces in the library had lower overall concentrations of particulate matter but also had extremely high levels of 92.8 and 85.7 μ g/m³ in the morning. The concentrations of thoracic-inhalable particulate matter in the canteen ranged from 26.4 to 56.8 μ g/m³, and the concentration of alveoli-inhalable particulate matter ranged from 22.7 to 35.6 μ g/m³. The concentrations of all three types of particulate matter in the library began to decrease in the morning, reaching a minimum of 12.3 μ g/m³ at 11:06 a.m., at 10:57 a.m., and 11:06 a.m. The concentrations of particulate matter at the two sites showed opposite trends at noon.

Feasibility Analysis of the Fuzzy Comprehensive Evaluation Model

Indoor air quality, as compared to other problems, is more complex, since there is virtually no full guarantee of a comprehensive result. As a result, indoor air quality evaluation is more dependent on the uncertainty pollutants that cause the risks. Decisions made in the face of limited contaminations may lead to mistakes. Moreover, current air assessment methods do not take into account interrelationship, leading to incorrect estimates. False assessments lead to high cost or professional healthy problems.

Indoor air quality involved medicine, building environment, and architectural design, there have been many mathematical assessment models, but these models have yet to be on the air quality evaluation system to quantify the influence extent of each factor in the description, therefore, it is necessary to improve on existing models, develop a new dynamic evaluation model and give the corresponding evaluation method, for making it applicable to different places or becoming the main basis of regulating and improving air quality.

In response to these facts, it was decided to carry out this research, with the main aim of developing a fuzzy model of assessment for indoor air quality in public buildings. The model will be a useful tool to support decision-making processes, especially in professional health problems which most authorities ignore.



The results of our study will also support the further development of methodologies for assessing other pollutants, taking into account biological and radioactive contaminations, including bacterial colony and Radon (Rn). Based on the classification standard for indoor environmental quality (58), this study combined the boundary values of each pollutant concentration and summarizes them in **Table 3** (54, 59).

NO₂ (ppm) 0.07 0.11 0.29 0.50 2.50

Level	IAQI	PM _{2.5} (mg/m ³)	PM ₁₀ (mg/m ³)	CO (ppm)	O ₃ (ppm)	SO ₂ (ppm)
I	50	0.010	0.033	2.0	0.002	0.04
11	100	0.019	0.055	5.5	0.01	0.07
111	150	0.038	0.091	9.3	0.05	0.13
IV	200	0.075	0.150	23.1	0.10	0.18
V	300	0.290	0.411	50	0.25	0.25

TABLE 3 | Threshold of indoor air chemical pollutants.

TABLE 4 | Air quality field test data.

Site	PM _{2.5} (μg/m³)	ΡΜ₁₀ (μg/m³)	CO (ppm)	O ₃ (ppb)	SO ₂ (ppb)	NO ₂ (ppb)
Library	29.76	34.44	0.00	3.00	0.00	2.00
Canteen	25.30	50.50	0.82	21.00	0.00	8.00
Waiting hall	37.53	62.83	0.65	35.00	15.00	59.00
Department store	21.47	45.26	2.04	16.00	0.00	32.00

The air quality monitoring data of the four places with large amounts of people flowing through at noon were adopted, including a library (113.4019°E, 23.0439°N), a canteen (113.3904°E, 23.0485°N), a waiting hall (113.3502°E, 23.1761°N) and a department store (113.3983°E, 23.0688°N), as shown in **Table 4**. With the help of the MATLAB program, the maximum feature vector was calculated, and the consistency test was carried out. Finally, the sets $R_1 \sim R_4$ of the four sets of weights were obtained.

$$R_{1} = \begin{bmatrix} 0 & 0.4340 & 0.5660 & 0 & 0 \\ 0.9350 & 0.0650 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0.8750 & 0.1250 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0.2050 & 0.7950 & 0 & 0 & 0 \\ 0.2050 & 0.7950 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0.7250 & 0.2750 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0.7825 & 0.2175 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0.3750 & 0.6250 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0.3750 & 0.6250 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0.8700 & 0.1300 & 0 & 0 \\ 0 & 0.886 & 0.0114 & 0 & 0 & 0 \\ 0 & 0.8500 & 0.1500 & 0 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The membership degree of fuzzy set is used to describe the degree to which an element belongs to a fuzzy set. The larger

TABLE 5 | Comprehensive evaluation vector values of different sites.

I	II		IV	v
0.7183	0.1402	0.1415	0	0
0.4410	0.4348	0.1242	0	0
0.4000	0.2189	0.3811	0	0
0.4863	0.4587	0.0550	0	0
	I 0.7183 0.4410 0.4000 0.4863	I II 0.7183 0.1402 0.4410 0.4348 0.4000 0.2189 0.4863 0.4587	I II III 0.7183 0.1402 0.1415 0.4410 0.4348 0.1242 0.4000 0.2189 0.3811 0.4863 0.4587 0.0550	I II III IV 0.7183 0.1402 0.1415 0 0.4410 0.4348 0.1242 0 0.4000 0.2189 0.3811 0 0.4863 0.4587 0.0550 0

the membership is, the higher the degree that the element belongs to the fuzzy set is, and vice versa. In some cases, the maximum membership principle will cause substantial information loss, so it cannot be objectively and effectively evaluated, and there may be one-sided results. In this paper, the b_j obtained from **Table 5** was used for reference to improve the fuzzy evaluation weighted-average grade method (60, 61), and the weighted average was determined according to formula (7) to make the evaluation grade quantifiable and more intuitive.

$$J = \sum_{i=1}^{m} (100 - 20(j-1)) \cdot b_j \tag{7}$$

Here, *J* is the grading value, and $0 \le J \le 100$. Setting the separation points at four values of 50, 60, 70 and 85 corresponds to the five grade intervals. The higher was the value, the closer it was to reaching level I (i.e., $0 \le J \le 50$, level V; $50 \le J \le 60$, level IV; $60 \le J \le 70$, level III; $70 \le J \le 85$, level II; $85 \le J \le 100$, level I). The weighted average level for calculating the level of the library value J_1 was 91.536 (level I), and the level of the canteen evaluation value J_2 was 86.336 (level I). The level of the waiting hall evaluation value J_3 was 80.378 (level II), and the level II), and the level of the department store evaluation value J_4 was 88.626 (level I).

CONCLUSIONS

By taking contamination risks as the evaluation indexes and considering the uncertainty of the evaluation indexes and the fuzziness of threshold, the method of indoor air quality evaluation is proposed. This method can make the best of each factor to make decisions for long-term health assessments. Based on fuzzy theory, the evaluation index weight can be obtained, combining with medical literature. The results reflect the impact of valuation indicators on indoor air assessment in the evaluation system of monitoring contaminations. This model modifies the evaluation function by introducing the boundary values of each pollutant concentration, which reduces the error caused by the mutual interference in evaluation indexes to some degree. The cases of the public buildings show that the indoor air assessment model can evaluate the exposed risk of practitioners properly, and the evaluation results are in accordance with the actual condition.

By analyzing the measured data of indoor and outdoor chemical pollutant concentrations in public buildings in Guangzhou, several conclusions can be drawn as follows:

- (1) Indoor particulate matter and outdoor particulate matter in the library showed obvious synchronism. PM2.5 and PM10 both showed a trend of first decreasing, then increasing and finally decreasing during the test. The PM₁₀ concentration in the library and canteen peaked at 07:45 in the morning and at 16:11, respectively (48.9 and 59 μ g/m³). The PM_{2.5} concentration in the library was higher than the outdoor concentration in the period beyond 9:00~13:00, and the PM₁₀ concentration in the canteen changed sharply and was frequently higher than the outdoor value. The PM_{2.5} concentrations in the canteen reached extreme values during the cooking periods before breakfast, lunch, and dinner, which were 32.5, 30.6, and 30.3 μ g /m³, respectively. The primary indoor pollutant was particulate matter, while the primary outdoor pollutant was CO. The NO concentration in the library fluctuated more violently, and CO₂ in the canteen peaked twice in the morning and at noon.
- (2) The Pearson correlation coefficient of the PM_{10} and $PM_{2.5}$ concentrations in the library was 0.98, and PM_{10} and SO_2 in the canteen were negatively correlated, with a correlation coefficient of -0.65. Although the Pearson correlation coefficients of the same chemical pollutants in different public buildings may vary greatly, $PM_{2.5}$ and PM_1 were always highly positively correlated, O_3 in the library was weakly positively correlated with other pollutants, and $PM_{2.5}$ and PM_1 in the canteen were almost negatively correlated with other pollutants.
- (3) The largest concentrations of PM_{10} in the library were 26.5 and 16.6 μ g/m³, accounting for 1.68% of the total data. The larger was the particle size in the canteen, the higher was the concentration observed. The concentration distribution in the library was relatively regular, with a significant peak and valley period, which was consistent with the variation trend in the outdoor particle concentration. The particles in the canteen were relatively dispersed during the day, and there were no periods when the particle size was too concentrated.

- (4) The high concentration of particles in the library was associated with the small particle size range $(0.25 \sim 0.45 \,\mu\text{m})$, while the high concentration of particles in the canteen was associated with the medium particle size range of $2.0 \sim 8.5 \,\mu\text{m}$. The mass concentration of PM₁₀ in the canteen was 1.52 times higher than that in the library. When choosing particle purification equipment, the particle size removal efficiency can be considered in a targeted way. The library prefers the removal of fine particles, while the canteen prefers the removal of large particles.
- (5) The level of the library was calculated using the fuzzy comprehensive evaluation method for level I, and the level of the waiting hall was calculated for level II. Although some sites were clean, both sites were cautious about a sharp increase in particulate matter. The pollutants in the library and the canteen in the morning mainly came from outdoors, while the PM_{10} content in the canteen at noon was relatively high; thus, the times of operating indoor air purification equipment can be concentrated during these periods. The staff should avoid staying indoors too much at peak concentration times, because at these times, the indoor pollutant concentrations were higher than the outdoor concentrations, and it is suggested that the air exchange times be strengthened and that other protective measures be taken.

Further analytical work is needed to investigate how the effect of the ultrafine particles or the submicron particles impacts other contamination in buildings and any potential changes in health impacts. Additionally, systematic measurements are needed to separate the impacts of VOCs from different public spaces on general population health and source control, to raise awareness of the potential impacts of indoor pollutants. These chemicals are subject to reactions with other species, as such research to suggest optimal strategies considering all indoor pollutants present are needed. Therefore, the evidence comes down to the need for health-based guideline values for as much contamination as possible, rather than an individual pollutant limit value.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

XL conceived of the study, designed and completed the experiments, participated in data analysis and interpretation, prepared figures, and wrote the manuscript. ZL assisted in writing review, editing, and performing the analysis with constructive discussions. HZ helped perform the experiments

and contributed conceptually to the project. XH analyzed the data and provided the software for completing the work. All authors read and approved the final manuscript.

FUNDING

This research was funded by the Natural Science Foundation of Guangdong Province, China, Grant Number 2016A030313711. This study would not be possible without the valuable support from the Library and the Fourth Canteen of Guangdong University of Technology. This research also received support from Guangzhou Traffic Group Tianhe Passenger Transport Terminal and Guangzhou GOGO Xintiandi Shopping Mall.

REFERENCES

- Morawska L, Afshari A, Bae GN, Buonanno G, Chao CYH, Hanninen O, et al. Indoor aerosols: from personal exposure to risk assessment. *Indoor Air.* (2013) 23:462–87. doi: 10.1111/ina.12044
- Klepeis NE, Nelson WC, Ott WR, Robinson JP, Tsang AM, Switzer P, et al. The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *J Exp Sci Environ Epidemiol*. (2001) 11:231–52. doi: 10.1038/sj.jea.7500165
- Brasche S, Bischof W. Daily time spent indoors in German homes Baseline data for the assessment of indoor exposure of German occupants. (2005). doi: 10.1016/j.ijheh.2005.03.003
- Bernstein JA, Alexis N, Bacchus H, Bernstein IL, Fritz P, Horner E, et al. The health effects of nonindustrial indoor air pollution. *J Allergy Clin Immunol.* (2008) 121:585–91. doi: 10.1016/j.jaci.2007.10.045
- Dobbin NA, Sun L, Wallace L, Kulka R, You H, Shin T, et al. The benefit of kitchen exhaust fan use after cooking - An experimental assessment. *Build Environ.* (2018) 135:286–96. doi: 10.1016/j.buildenv.2018.02.039
- Logue JM, Klepeis NE, Lobscheid AB, Singer BC. Pollutant exposures from natural gas cooking burners: a simulation-based assessment for Southern California. *Environ Health Perspect.* (2014) 122:43–50. doi: 10.1289/ehp.1306673
- Yadav IC, Devi NL, Li J, Zhang G. Occurrence and source apportionment of halogenated flame retardants in the indoor air of Nepalese cities: implication on human health. *Atmospheric Environ.* (2017) 161:122–31. doi: 10.1016/j.atmosenv.2017.04.031
- Dong G-H. Perspective for future research direction about health impact of ambient air pollution in China. Adv Exp Med Biol. (2017) 1017:263–8. doi: 10.1007/978-981-10-5657-4_12
- Amoatey P, Omidvarborna H, Baawain MS, Al-Mamun A. Indoor air pollution and exposure assessment of the gulf cooperation council countries: a critical review. *Environ Int.* (2018) 121:491–506. doi: 10.1016/j.envint.2018.09.043
- Hu T, Jia W, Cao J, Huang R, Li H, Liu S, et al. Indoor air quality at five site museums of Yangtze River civilization. *Atmospheric Environ*. (2015) 123:449–54. doi: 10.1016/j.atmosenv.2015.10.022
- Sciences IAOIA. Deadly household pollution: a call to action. Indoor Air. (2006) 16:2–3. doi: 10.1111/j.1600-0668.2005.00416.x
- Danesh Yazdi M, Wang Y, Di Q, Zanobetti A, Schwartz J. Long-term exposure to PM2.5 and ozone and hospital admissions of Medicare participants in the Southeast USA. *Environ Int.* (2019) 130:104879. doi: 10.1016/j.envint.2019.05.073
- Huang J, Song Y, Chu M, Dong W, Miller MR, Loh M, et al. Cardiorespiratory responses to low-level ozone exposure: the in Door Ozone Study in childrEn (DOSE). *Environ Int.* (2019) 131:105021. doi: 10.1016/j.envint.2019. 105021
- Franck U, Herbarth O, Röder S, Schlink U, Borte M, Diez U, et al. Respiratory effects of indoor particles in young children are size dependent. *Sci Total Environ.* (2011) 409:1621–31. doi: 10.1016/j.scitotenv.2011.01.001

ACKNOWLEDGMENTS

The authors would like to thank Mr. Fujun Pan, Haoran Huang, Jingxuan Yang, Shiying Lan and the other members of the research group from Guangdong University of Technology for their assistance in data collecting and processing.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh. 2021.579299/full#supplementary-material

- Norbäck D, Lu C, Zhang Y, Li B, Zhao Z, Huang C, et al. Onset and remission of childhood wheeze and rhinitis across China — Associations with early life indoor and outdoor air pollution. *Environ Int.* (2019) 123:61–9. doi: 10.1016/j.envint.2018.11.033
- Oliveira M, Slezakova K, Delerue-Matos C, Pereira MC, Morais S. Children environmental exposure to particulate matter and polycyclic aromatic hydrocarbons and biomonitoring in school environments: a review on indoor and outdoor exposure levels, major sources and health impacts. *Environ Int.* (2019) 124:180–204. doi: 10.1016/j.envint.2018.12.052
- Tavera Busso I, Mateos AC, Juncos LI, Canals N, Carreras HA. Kidney damage induced by sub-chronic fine particulate matter exposure. *Environ Int.* (2018) 121:635–42. doi: 10.1016/j.envint.2018.10.007
- Stowell JD, Geng G, Saikawa E, Chang HH, Fu J, Yang C-E, et al. Associations of wildfire smoke PM2.5 exposure with cardiorespiratory events in Colorado 2011–2014. Environ Int. (2019) 133:105151. doi: 10.1016/j.envint.2019.105151
- da Costa e Oliveira JR, Base LH, de Abreu LC, Filho CF, Ferreira C, Morawska L. Ultrafine particles and children's health: literature review. *Paediatr Respir Rev.* (2019) 32:73–81. doi: 10.1016/j.prrv.2019.06.003
- Tang X, Bai Y, Duong A, Smith MT, Li L, Zhang L. Formaldehyde in China: production, consumption, exposure levels, and health effects. *Environ Int.* (2009) 35:1210–24. doi: 10.1016/j.envint.2009.06.002
- Sarigiannis DA, Karakitsios SP, Gotti A, Liakos IL, Katsoyiannis A. Exposure to major volatile organic compounds and carbonyls in European indoor environments and associated health risk. *Environ Int.* (2011) 37:743–65. doi: 10.1016/j.envint.2011.01.005
- Buoli M, Grassi S, Caldiroli A, Carnevali GS, Mucci F, Iodice S, et al. Is there a link between air pollution and mental disorders? *Environ Int.* (2018) 118:154–68. doi: 10.1016/j.envint.2018.05.044
- Kioumourtzoglou MA, Power MC, Hart JE, Okereke OI, Coull BA, Laden F, et al. The association between air pollution and onset of depression among middle-aged and older women. *Am J Epidemiol.* (2017) 185:801–9. doi: 10.1093/aje/kww163
- 24. Andersen ZJ, Stafoggia M, Weinmayr G, Pedersen M, Galassi C, Jørgensen JT, et al. Long-term exposure to ambient air pollution and incidence of postmenopausal breast cancer in 15 European Cohorts within the ESCAPE Project. *Environ Health Perspect*. (2017) 125:919. doi: 10.1289/EHP1742
- Andersen ZJ, Ravnskjaer L, Andersen KK, Loft S, Brandt J, Becker T, et al. Long-term exposure to fine particulate matter and breast cancer incidence in the Danish Nurse Cohort Study. *Cancer Epidemiol Biomarkers Prevent*. (2016) 26:428–30. doi: 10.1158/1055-9965.EPI-16-0578
- 26. Goldberg MS, Villeneuve PJ, Crouse D, To T, Weichenthal SA, Wall C, et al. Associations between incident breast cancer and ambient concentrations of nitrogen dioxide from a national land use regression model in the Canadian National Breast Screening Study. *Environ Int.* (2019) 133:105182. doi: 10.1016/j.envint.2019.105182
- Atkinson RW, Carey IM, Kent AJ, van Staa TP, Anderson HR, Cook DG. Long-term exposure to outdoor air pollution and incidence of cardiovascular diseases. *Epidemiology*. (2013) 24:44–53. doi: 10.1097/EDE.0b013e3182 76ccb8

- Li X, Yi H, Wang H. Sulphur dioxide and arsenic affect male reproduction via interfering with spermatogenesis in mice. *Ecotoxicol Environ Safety.* (2018) 165:164–73. doi: 10.1016/j.ecoenv.2018.08.109
- Zhang J, Li Z, Qie M, Zheng R, Shetty J, Wang J. Sodium fluoride and sulfur dioxide affected male reproduction by disturbing blood-testis barrier in mice. *Food Chem Toxicol.* (2016) 94:103–11. doi: 10.1016/j.fct.2016.05.017
- Shrubsole C, Dimitroulopoulou S, Foxall K, Gadeberg B, Doutsi A. IAQ guidelines for selected volatile organic compounds (VOCs) in the UK. *Build Environ.* (2019) 165:106382. doi: 10.1016/j.buildenv.2019.106382
- Azuma K, Jinno H, Tanaka-Kagawa T, Sakai S. Risk assessment concepts and approaches for indoor air chemicals in Japan. *Int J Hygiene Environ Health*. (2020) 225:113470. doi: 10.1016/j.ijheh.2020.113470
- Fanger PO. Introduction of the olf and the decipol units to quantify air pollution perceived by humans indoors and outdoors. *Energy Build*. (1988) 12:1–6. doi: 10.1016/0378-7788(88)90051-5
- Thach T-Q, Tsang H, Cao P, Ho L-M. A novel method to construct an air quality index based on air pollution profiles. *Int J Hygiene Environ Health*. (2018) 221:17–26. doi: 10.1016/j.ijheh.2017.09.012
- Zhu C, Li N. Study on Grey Clustering Model of Indoor Air Quality Indicators. Proc Eng. (2017) 205:2815–22. doi: 10.1016/j.proeng.2017.09.895
- Quang TN, He C, Morawska L, Knibbs LD. Influence of ventilation and filtration on indoor particle concentrations in urban office buildings. *Atmospheric Environ.* (2013) 79:41–52. doi: 10.1016/j.atmosenv.2013. 06.009
- 36. Kim S-S, Kang D-H, Choi D-H, Yeo M-S, Kim K-W. Comparison of strategies to improve indoor air quality at the pre-occupancy stage in new apartment buildings. *Build Environ.* (2008) 43:320–8. doi: 10.1016/j.buildenv.2006.03.026
- Lin BY, Huangfu YB, Lima N, Jobson B, Kirk M, O'Keeffe P, et al. Analyzing the relationship between human behavior and indoor air quality. *J Sens Actuar Netw.* (2017) 6:18. doi: 10.3390/jsan6030013
- Luo N, Weng W, Xu X, Hong T, Fu M, Sun K. Assessment of occupantbehavior-based indoor air quality and its impacts on human exposure risk: a case study based on the wildfires in Northern California. *Sci Total Environ*. (2019) 686:1251–61. doi: 10.1016/j.scitotenv.2019.05.467
- Brantley HL, Hagler GSW, Kimbrough ES, Williams RW, Mukerjee S, Neas LM. Mobile air monitoring data-processing strategies and effects on spatial air pollution trends. *Atmospheric Measur Tech.* (2014) 7:2169–83. doi: 10.5194/amt-7-2169-2014
- 40. Bossche JVD, Peters J, Verwaeren J, Botteldooren D, Theunis J, Baets BDJAE. Mobile monitoring for mapping spatial variation in urban air quality: development and validation of a methodology based on an extensive dataset. *Atmospheric Environ.* (2015) 105:148–61. doi: 10.1016/j.atmosenv.2015.01.017
- Aihua H, Zhongliang D, Yao Z, editors. Study on the method of indoor wireless channel characteristic measurement and analysis based on Vector Network Analyzer. In: 13th IEEE International Conference on Electronic Measurement & Instruments (ICEMI). (2017). doi: 10.1109/ICEMI.2017.8265965
- 42. Pei Y, Guo M. The fundamental principle and application of sliding average method. *Gun Launch Control.* (2001) 1:21–3.
- Zhao C, Chen J, Du P, Yuan H. Characteristics of climate change and extreme weather from 1951 to 2011 in China. *Int J Environ Res Public Health.* (2018) 15:2540. doi: 10.3390/ijerph15112540
- 44. Liu GR, Nguyen TT. Smoothed Finite Element Methods. Boca Raton, FL: Taylor & Francis (2010).
- Ziemba PJE. Multi-criteria fuzzy evaluation of the planned offshore wind farm investments in Poland. *Energies*. (2021) 14:978. doi: 10.3390/en14040978

- Chen JF, Hsieh HN, Do QH. Evaluating teaching performance based on fuzzy AHP and comprehensive evaluation approach. *Appl Soft Comput.* (2015) 28:100–8. doi: 10.1016/j.asoc.2014.11.050
- Lin Y, Lin C, Qiu X. Fuzzy Comprehensive evaluation method of masonry structure safety based on grey clustering theory. *Math Problems Eng.* (2018) 2018:10192. doi: 10.1155/2018/8710192
- Zhao H, Yao L, Mei G, Liu T, Ning Y. A fuzzy comprehensive evaluation method based on AHP and entropy for a landslide susceptibility map. *Entropy*. (2017) 19:396. doi: 10.3390/e19080396
- Javid A, Hamedian AA, Gharibi H, Sowlat MH. Towards the application of Fuzzy Logic for Developing a Novel Indoor Air Quality Index (FIAQI). *Iranian J Public Health*. (2016) 45:203–13.
- Sowlat MH, Gharibi H, Yunesian M, Mahmoudi MT, Lotfi S. A novel, fuzzy-based air quality index (FAQI) for air quality assessment. *Atmospheric Environ.* (2011) 45:2050–9. doi: 10.1016/j.atmosenv.2011.01.060
- Long L, Li ZD. An assessment model of monitoring risk in deep excavation based on fuzzy theory. *Indoor Built Environ.* (2020) 29:221–9. doi: 10.1177/1420326X19856671
- Onkal-Engin G, Demir I, Hiz H. Assessment of urban air quality in Istanbul using fuzzy synthetic evaluation. *Atmospheric Environ.* (2004) 38:3809–15. doi: 10.1016/j.atmosenv.2004.03.058
- 53. Feng N, Fu B. Indoor air quality evaluation method and its mathematical model. *J Suzhou Univ Sci Technol.* (2015) 32:9–14.
- Ming L, lin L, chang S, wenbo D. The study on the theory of grade division of fuzzy comprehensive evaluation of indoor environment. *Low Temp Architect Technol.* (2018) 40:109–24.
- 55. Xiao K, Yuku W, Guang W, Bin F, Yuanyuan Z. Spatiotemporal Characteristics of Air Pollutants (PM10, PM2.5, SO2, NO2, O3, and CO) in the Inland Basin City of Chengdu, Southwest China. *Atmosphere*. (2018) 9:74. doi: 10.3390/atmos9020074
- Du B, Gao J, Chen J, Stevanovic S, Ristovski Z, Wang L, et al. Particle exposure level and potential health risks of domestic Chinese cooking. *Build Environ*. (2017) 123:564–74. doi: 10.1016/j.buildenv.2017.07.031
- 57. Standards BSIB. Workplace Atmospheres. Size Fraction Definitions for Measurement of Airborne Particles. London: BSI British Standards (1993).
- Ting-yun H. Development of Indoor-Vehicle Air Quality Index System. Taipei: National Taipei University of Technology (2003).
- Zhu C. Reasearch on Comfort Evaluation and Grey Theory Analysis of Indoor Environment. Changsha: Hunan University (2012).
- 60. Zadeh MA, Sadrania A, Zibandeh M, Rostami P, editors. Determining a suitable location for a Sewage Treatment Plant using a new fuzzy weighted average (FWA) method based on left and right scores. In: *13th Iranian Conference.* Qazvin: IEEE (2013).
- Jie Z, Xin-ze L, Ai-ying K, Yuan H, Guo-quan Z. Application of fuzzy synthetic evaluation method in nanxi river water quality evaluation. *Zhejiang Hydrotech.* (2018) 46:8–28.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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