



The impact of particulate matter on allergy risk among adults: integrated exposure assessment

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Abstract

Exposure assessment is an important part in environmental epidemiology for determining the associations of environmental factors with health effects. One of the greatest challenges for personal exposure assessment is associated with peoples' mobility during the day and spatial and temporal dynamics of air pollution. In this study, the impact of PM₁₀ (particulate matter less than 10 µm) on allergy risk among adults was assessed using objective methods of exposure assessment. The primary objective of the present study was to estimate personal exposure to PM₁₀ based on individual daily movement patterns. Significant differences between the concentration of PM₁₀ in different microenvironments (MEs) and personal exposure to PM₁₀ were determined. Home exposure accounted for the largest part of PM₁₀ exposure. Thirty-five percent of PM₁₀ exposure was received in other non-home MEs. Allergy risk increased significantly with increasing exposure to PM₁₀. Adults exposed to the highest levels of PM₁₀ exposure had a twice-higher risk of allergies than adults exposed to the lowest levels of PM₁₀ exposure. The study results have practical relevance for exposure assessment to environmental factors and its impact on health effects.

Keywords Particulate matter · PM₁₀ · Exposure assessment · Allergy risk · Microenvironment · GPS

Introduction

The effects of exposure to environmental risk factors on human health raise concerns around the world (WHO 2016). Air pollution is one of the most important environmental issues resulting from the urbanisation, and it is one of the main causes for decreasing quality of life in cities (Giovanis and Ozdamar 2018; Silva et al. 2016). Air pollution is growing worse in urban areas due to the unbalanced development of urban spaces and the significant increase in emissions from mobile and stationary sources. Exposure to particulate matter can affect the human respiratory system and have an adverse effect on respiratory disease including asthma, allergic rhinitis, and other allergic respiratory diseases (Darçın 2014; Guarnieri and Balmes 2014; Kim et al. 2013). The prevalence

of allergic diseases is increasing worldwide, and such a rapid spread cannot be explained solely by genetic factors (Maio et al. 2016). There is evidence that air pollution may interact with airborne allergens enhancing the risk of atopic sensitization and exacerbation of symptoms in sensitised subjects, and this interaction may have a synergistic or additive effect on the risk of allergies (Baldacci et al. 2015). However, there is insufficient evidence at a population level.

Exposure assessment is essential for determining the relationship between air pollution and health effects (Nieuwenhuijsen et al. 2006; Semple 2005). One of the biggest challenges facing environmental epidemiology today is the dynamic nature of exposure (Steinle et al. 2015). Individuals constantly move in time and space, while air pollution at the same time is highly variable, both spatially and temporally. Better understanding of personal exposure as a person moves through his or her daily life considering all microenvironments (MEs) where people spend their time is important to improve health impact assessment (Devi et al. 2013; Dewulf et al. 2016).

Air pollution dispersion modelling is one of the most effective and widely used methods of ambient air quality assessment, which allows calculating or predicting air pollution level and enables the illustration of air pollutants spatial

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dispersion at different urban scales. By contrast, air pollution measurements give information only about a very limited situation and can only describe air quality at specific location and time, without giving clear guidance on the identification of the causes of the air quality problem (Dèdelè and Miškinytė 2015). Air pollution dispersion modelling, geographic information system (GIS), and novel sensing technologies (global positioning systems (GPS) and accelerometer sensors) integrated into smartphones are used to improve personal exposure assessment in environmental exposure and health studies (de Nazelle et al. 2013; Reis et al. 2015). Using geospatial methods, we can assess personal exposure to environmental factors more accurately including individual-level daily movement patterns.

In this study, the impact of PM₁₀ (particulate matter less than 10 µm) exposure on allergy risk in adults is assessed using objective methods of exposure assessment. Two important topics are addressed in the present study: first, the exposure assessment using integrated methods, and second, the effect of PM₁₀ on allergy risk in adults. The primary objective of this study was to estimate personal exposure to PM₁₀ using individual daily movement patterns and exposure models applied to different MEs and then, after controlling for a number of potential confounders, to assess the association between personal exposure to PM₁₀ and allergy risk.

Material and methods

Study design and population characteristic

An epidemiological case-control study included adults from Kaunas city, Lithuania. The data used in this study were collected as part of the PHENOTYPE (Positive health effects of the natural outdoor environment in typical populations in different regions in Europe) project (Nieuwenhuijsen et al. 2014). The participants were adults recruited between 2013 and 2014 in Kaunas city, Lithuania. In total, 4672 adults were approached by postal mail to fill out questionnaires and to participate in the study. Responses to the postal questionnaires were received from 1141 individuals of Kaunas city aged 18–86 years. The study was approved by the Lithuanian Bioethics Committee, and informed consent was obtained from all participants.

The data were collected in two steps in the study population: a questionnaire survey among all participants of Kaunas cohort ($n = 1141$) and a subsample of 125 people (smartphone study) who had completed the questionnaire survey as well. One hundred twenty-five participants were randomly selected from all study population of Kaunas cohort to participate in a smartphone study using objective measures and standardised questionnaires in order to assess the individual exposure to PM₁₀. The study design is presented in Fig. 1 and Table 1.

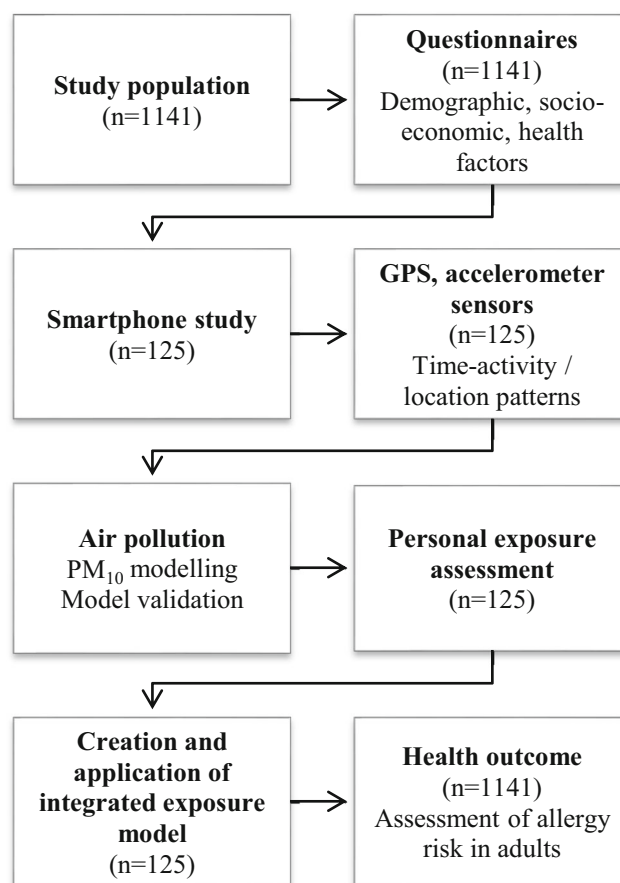


Fig. 1 Study design

Characteristics of Kaunas cohort

Kaunas cohort comprised 1141 adults who filled questionnaires. Of the 1141 study participants, 56% were women, 6% were younger than 45 years of age, 36% were between 45 and 65 years of age, and 58% were older than 65 years of age. Individuals were highly educated (66.3%), 38% of participants had higher incomes than average, 25% were full-time workers, 9% were part-time workers, and 66% were unemployed, retired, or others. In this study, 41.4% of participants were overweight and 27% were obese. The prevalence of chronic disease in adults was 75.8%. There were 63.6% of participants who never smoked, 27.0% were former smokers, and 9.8% were current smokers.

There were no significant differences in gender, nationality, and educational level of the entire Kaunas cohort and the participants from the smartphone study. However, the participants of the smartphone study were younger and differed on occupational status. The prevalence of allergic diseases was not significantly different between the entire Kaunas cohort (8.2%) and the smartphone study participants (6.4%).

Table 1 Demographic characteristics of study participants

Characteristic	Kaunas cohort (<i>n</i> = 1141) <i>N</i> (%)	Smartphone study participants (<i>n</i> = 125) <i>N</i> (%)
Age		
< 45	67 (5.9)	47 (37.6)
45–65	411 (36.0)	54 (43.2)
> 65	663 (58.1)	24 (19.2)
<i>p</i> value	< 0.001	< 0.001
Gender		
Male	497 (43.6)	55 (44.0)
Female	643 (56.4)	70 (56.0)
<i>p</i> value	< 0.001	< 0.001
Marital status		
Married	717 (63.0)	73 (58.4)
Divorced	136 (11.9)	17 (13.6)
Single	70 (6.1)	27 (21.6)
Widowed	216 (19.0)	8 (6.4)
<i>p</i> value	< 0.001	< 0.001
Education level		
Primary school	50 (4.4)	1 (0.8)
Secondary school	368 (32.3)	34 (27.2)
University degree	720 (63.3)	90 (72.0)
<i>p</i> value	< 0.001	< 0.001
Occupational status		
Full-time	280 (24.7)	47 (37.6)
Part-time, student	102 (9.0)	36 (28.8)
Unemployed, retired, others	753 (66.3)	42 (33.6)
<i>p</i> value	< 0.001	< 0.001
Income		
Lower than average	696 (62.3)	52 (41.6)
Higher than average	421 (37.7)	73 (58.4)
<i>p</i> value	< 0.001	< 0.001
Ethnic group		
Lithuanian	1091 (96.3)	121 (96.8)
Other	42 (3.7)	4 (3.2)
<i>p</i> value	< 0.001	< 0.001
Body mass index		
Normal weight (< 24.9)	358 (31.6)	66 (54.1)
Overweight (25.0–29.9)	469 (41.4)	36 (29.5)
Obese (> 30.0)	305 (27.9)	20 (16.4)
<i>p</i> value	< 0.001	< 0.001
Chronic disease		
No	276 (24.2)	58 (46.4)
Yes	865 (75.8)	67 (53.6)
<i>p</i> value	< 0.001	< 0.001
Smoking		
Never smoker	720 (63.3)	65 (52.4)
Former smoker	307 (27.0)	34 (27.4)
Current smoker	111 (9.8)	25 (20.2)
<i>p</i> value	< 0.001	< 0.001
Allergic disease		
No	1047 (91.8)	117 (93.6)
Yes	94 (8.2)	8 (6.4)
<i>p</i> value	< 0.001	0.004

Personal exposure assessment

Smartphone study

The participants were recruited from the participants of the PHENOTYPE questionnaire survey (*n* = 1141) who had indicated that they were willing to volunteer in the

smartphone study. The participants carried a smartphone (Samsung Galaxy Mini) with an integrated CalFit system that runs on Android-based mobile phones and tracks time-location patterns of the study participants for seven complete days. This software uses the GPS and the accelerometer sensors that are installed in the phone to record physical activity, energy expenditure, time, and location in which an activity occurs. The collected data were analysed and used to assess personal exposure to PM₁₀. The CalFit application was developed by researchers of the University of California, Berkeley, for exposure assessment studies and validated in epidemiological studies (Donaire-Gonzalez et al. 2013; Seto et al. 2010). Participants were asked to complete a daily diary to record the time they put on or take the phone off, the reasons for not having the phone on, and the type of activity that they were doing. The data of time, geographic coordinates, and physical activity of study participants were collected every 10 s.

The assessment of personal exposure to PM₁₀

To assess the personal exposure to PM₁₀, the annual average map of PM₁₀ that was modelled using ADMS-Urban model, ArcGIS software, and individual data collected during smartphone study were used. The ADMS-Urban model was validated by comparing annual averaged ambient PM₁₀ concentrations predicted by this model with the measurement data of PM₁₀ at 20 sites in Kaunas city (Fig. 2). The measurements of PM₁₀ were a part of the European Study of Cohorts for Air Pollution Effects (ESCAPE) project (<http://www.escapeproject.eu/>). The correlation between the ambient PM₁₀ concentrations modelled using the ADMS-Urban model and the measurement data was high (*r* = 0.87) (Fig. 3). The average difference between modelled and measured PM₁₀ concentrations was 15%.

In this study, the exposure estimates were based on the concept of microenvironment (ME), which is defined as a space with a homogenous pollutant concentration (Duan 1982). Based on the time-activity/location patterns assessed using GPS and accelerometer sensors, six MEs (home, work, other indoor, static outdoor, walking, transit) were identified for each study participant to assess individual data and exposure profiles. The spatial analysis of collected data was performed using ArcGIS software, topographic and orthophoto maps, and building layers.

PM₁₀ concentrations for six MEs were estimated using ADMS-Urban air pollution dispersion model (Fig. 4). The residence and work addresses of each study participant were geocoded using ArcGIS software, and the annual average modelled concentration of PM₁₀ was assigned to each address.

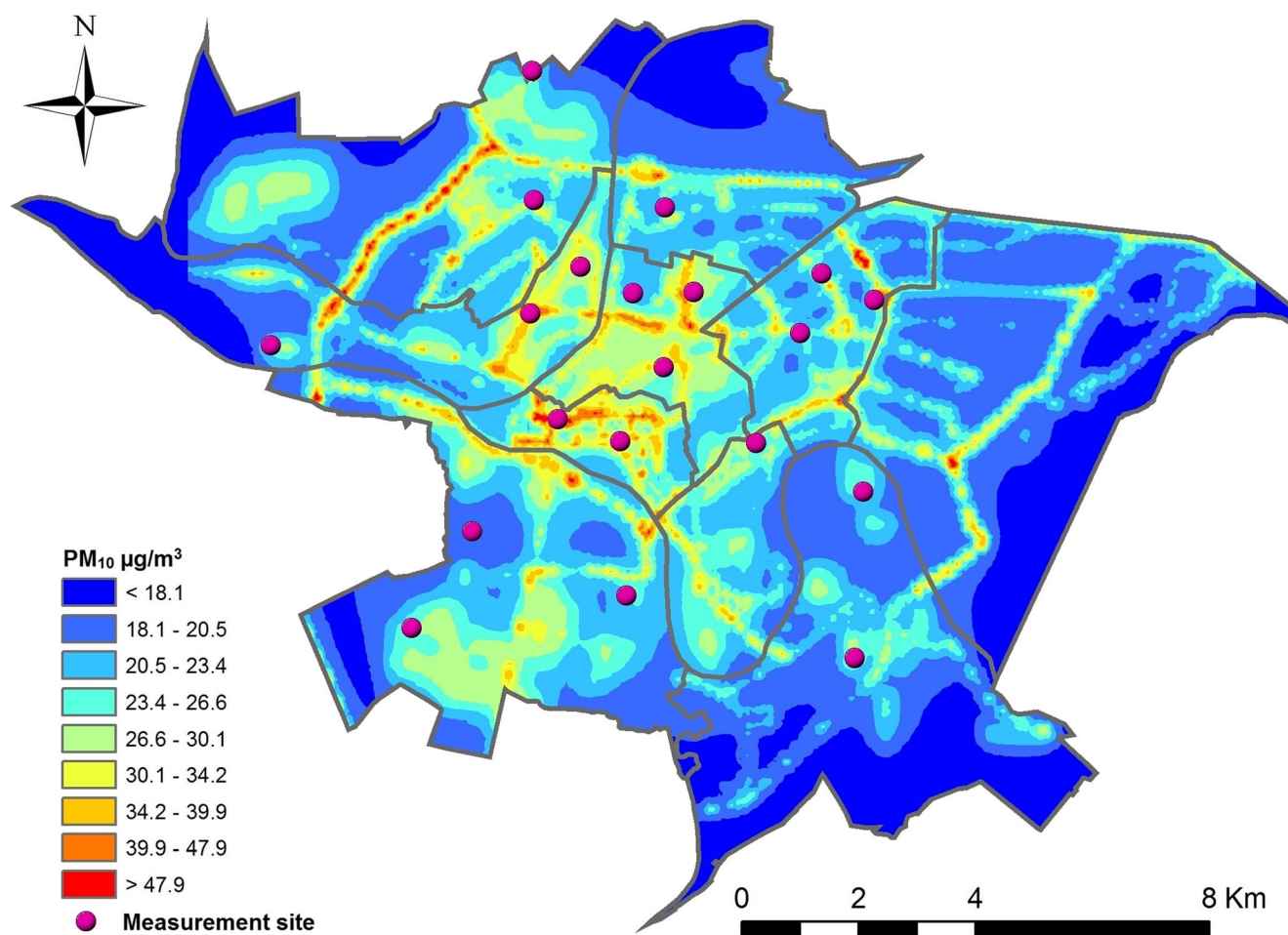


Fig. 2 Modelled PM₁₀ concentration and measurement sites in Kaunas city

Personal exposure to PM₁₀ was assessed based on PM₁₀ concentrations in MEs and the time spent in them. The calculation of time-weighted integrated exposure (E_i) to PM₁₀ (Kornatit et al. 2010):

$$E_i = \sum C_j \times t_{ij} \quad (1)$$

where E_i is the time-weighted integrated exposure, C_j is the PM₁₀ concentration in each microenvironment, and t_{ij} is the fraction of 24 h spent in each environment.

Outcome assessment in adults

Questionnaire responses by study participants were used to categorise demographic, residence, job, socioeconomic, health, personal habits, housing, and environmental characteristics. We also asked the study participants to report their age (younger than 45, 45–65 years, and more), educational level (primary, secondary, or university), marital status (married, single, divorced, or widowed), occupational status (working full-time; working part-time, student; or unemployed, retired, others), income (lower than average or higher than average), body mass index (< 25 kg/m², 25–30 kg/m², or > 30 kg/m²), smoking (non-smoker, former smoker, smoker), and other variables.

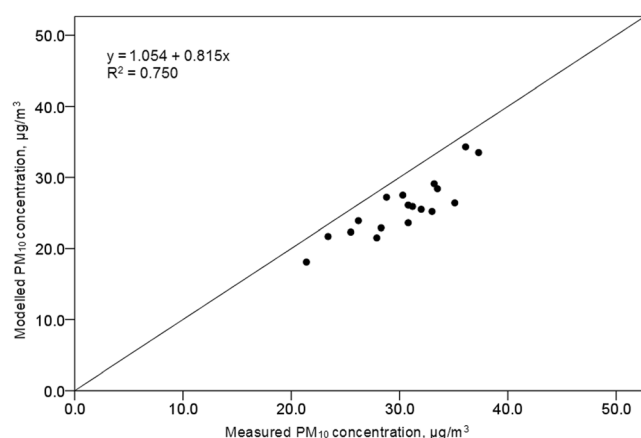


Fig. 3 The relationship between ambient concentrations of PM₁₀ modelled using ADMS-Urban model and measured using Harvard Impactors

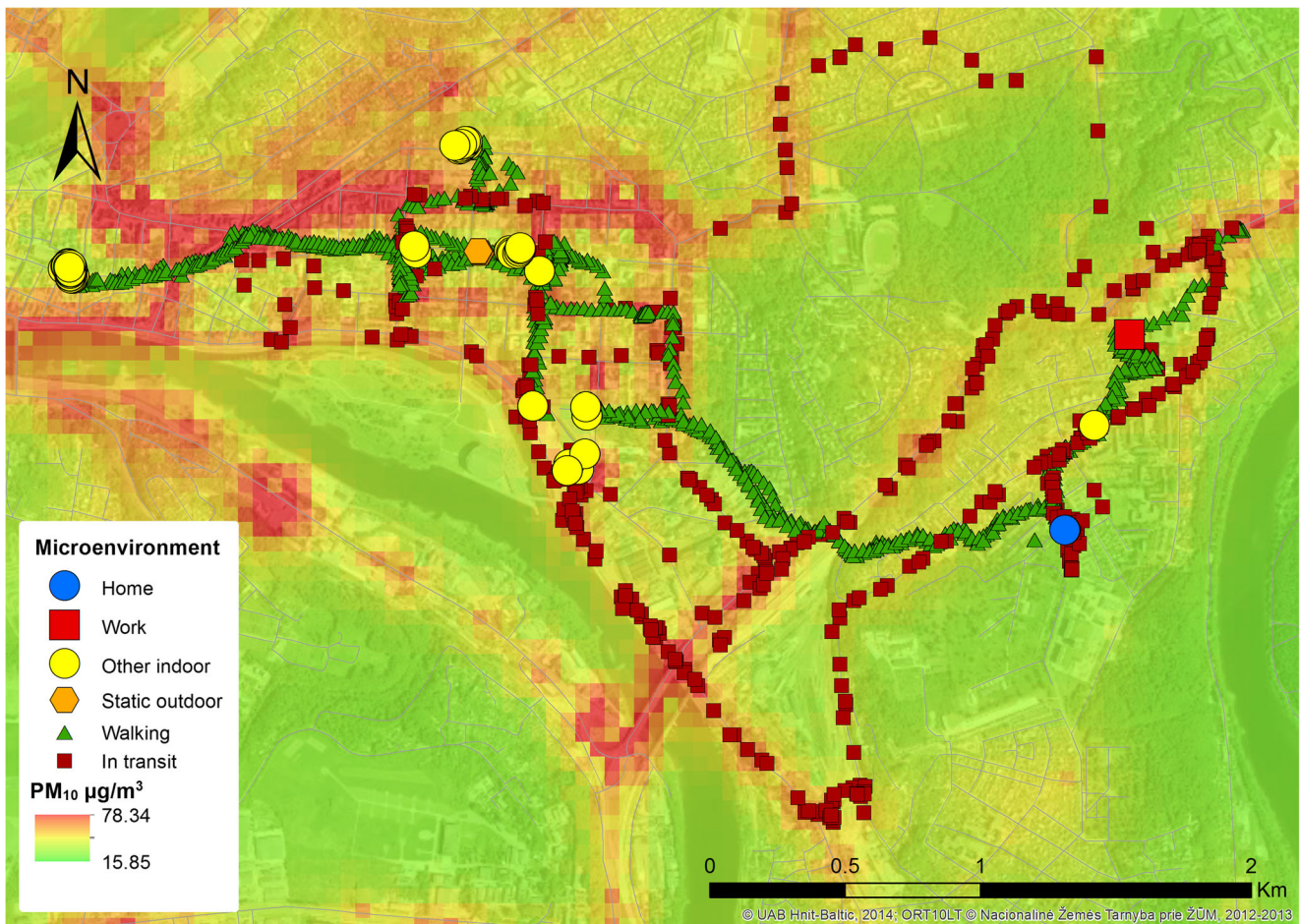


Fig. 4 GPS tracking of a participant (different colour represents different microenvironments); background shading is PM_{10} concentration

Responses to the standardised International questionnaire completed by study participants were used to identify individuals with allergic diseases. Allergy was identified by an affirmative response to the question: have you been doctor-diagnosed with allergies?

Statistical analysis

A linear regression analysis was used to create a linear model of integrated PM_{10} exposure. We performed an individual participants' data analysis and developed an integrated exposure model, which was used to evaluate the exposure of PM_{10} for the entire Kaunas cohort and to assess the association of PM_{10} exposure with the risk of allergies. Indicators with the highest statistically significant impact on PM_{10} exposure estimation model were selected. The dependent variable was personal exposure of PM_{10} , and the independent variables were PM_{10} concentration at home, travel frequency, dog ownership, and greenness around residence place. Based on the individual data (such as car disposal and the frequency of use, other types of vehicle disposal and the frequency of use, the use of public transport), a new variable named "Travel frequency" was

created for the model. To compare the means of two groups, *t* test and, in the case of small samples, a Mann-Whitney *U* test were performed. The Pearson correlation coefficient was used to determine the strength of the linear relationship between two normally distributed continuous variables, and the Spearman correlation coefficients was used when the variables were not normally distributed. The repeated measures analysis was performed to compare PM_{10} concentration and exposure in different microenvironments, based on demographic, social, and other factors.

Analyses of adult allergies

The association between personal exposure to PM_{10} and allergy risk in adults was analysed by multiple logistic regression, adjusting for confounding factors. We used the chi-square test to estimate individual-level categorical variables associated with allergies. To detect potential confounding variables, odds ratios (ORs) and confidence intervals (CIs) that were based on 0.95 confidence level were calculated. The testing of statistical hypothesis was done at 0.05 significance level. Recent literature on methods for identifying confounders suggest that a

factor can be a confounder even if it is not statistically significant by itself because it changes the effect of the exposure when it is included in the model, or because it is a confounder only when included with other factors (Skelly et al. 2012). In this study, the factor was considered a confounder if it changed the adjusted estimate from the crude estimate by approximately 10% (Lee 2014).

Multiple logistic regression models were developed to assess the relationship between personal exposure to PM₁₀ and allergy risk in adults, adjusting for age, gender, smoking, occupational status, health status, body mass index (BMI), the impact of physical or emotional health on social activities, and NO₂ exposure.

We used tertiles and interquartile range (IQR) to divide PM₁₀ exposure and to estimate odds ratios by using logistic regression models. The cut-off values of PM₁₀ exposure levels used were (1) < 23.2 µg/m³, (2) 23.2–25.6 µg/m³, and (3) > 25.6 µg/m³. We used exposure level in the 1st tertile as the reference category (low exposure). We provided an estimated odds ratio of allergy risk for one IQR increase of PM₁₀ exposure. The effect of PM₁₀ exposure on doctor-diagnosed allergies in adults was estimated as crude and adjusted odds ratios with 95% confidence intervals and *p* value.

All statistical analyses were performed using IBM SPSS software version 22.0 (SPSS Inc., Chicago, IL).

The creation of the map, the combination of data layers, and other spatial analysis of collected data were performed using ArcGIS software (version 10.3).

Results and discussion

The relationship between PM₁₀ concentration and exposure in different microenvironments

The main purpose of the individual-level smartphone study was to determine the concentration of PM₁₀ in different microenvironments and to assess personal exposure to PM₁₀ in each microenvironment based on time-activity/location patterns.

The study results demonstrated that the lowest average annual concentration of PM₁₀ was found in home ME (25.2 µg/m³) (Fig. 5). Home concentration of PM₁₀ ranged from 16.3 to 38.3 µg/m³. In work ME, the annual concentration of PM₁₀ varied from 19.5 to 41.5 µg/m³ and the mean value of PM₁₀ was higher by 3.2% compared to home ME. The average annual concentration of PM₁₀ in other indoor, outdoor, and walking MEs was similar and varied from 26.3 to 26.5 µg/m³. The results showed that the highest average annual concentration of PM₁₀ was determined in transit ME (29.0 µg/m³), and it was 15.1% and 11.5% higher than in home and work MEs, respectively.

A statistical analysis was performed to determine the differences between PM₁₀ concentrations in home ME and in all other microenvironments. The results showed that the

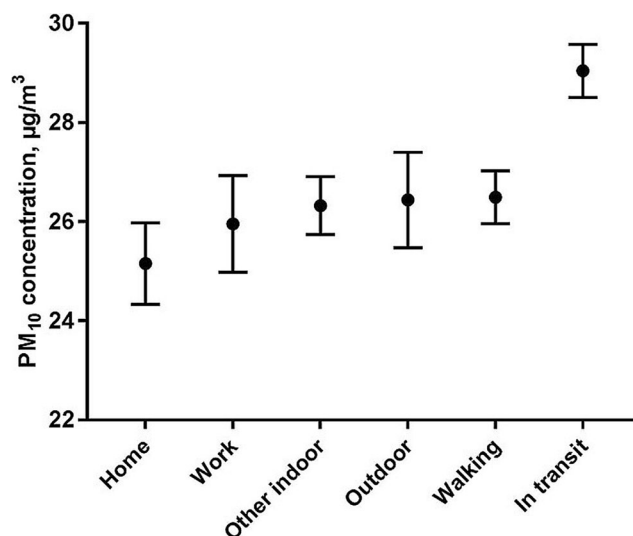


Fig. 5 Average annual concentration of PM₁₀ (mean ± SE) in different microenvironments

difference between home concentration of PM₁₀ and all other MEs (except for work ME) was statistically significant (*p* < 0.05). The greatest statistically significant difference in the average concentration of PM₁₀ was found between home and in transit MEs (*t* (116) = −10.01, *p* < 0.0001).

Personal exposure to PM₁₀ for each study participant was calculated by weighing the measurements of different microenvironments by the amount of time spent in each ME. We assessed each ME contribution to individual-level exposure to PM₁₀ using a time-weighted model. The results showed that the mean total personal exposure to PM₁₀ was 25.4 µg/m³. The mean home exposure to PM₁₀ was 18.9 µg/m³ and accounted for the largest portion (65.4%) of total personal exposure of PM₁₀ (Fig. 6). The results indicate that, on average, 35% of the total exposure of PM₁₀ is received in other non-home microenvironments. In this study, 19.0% of the

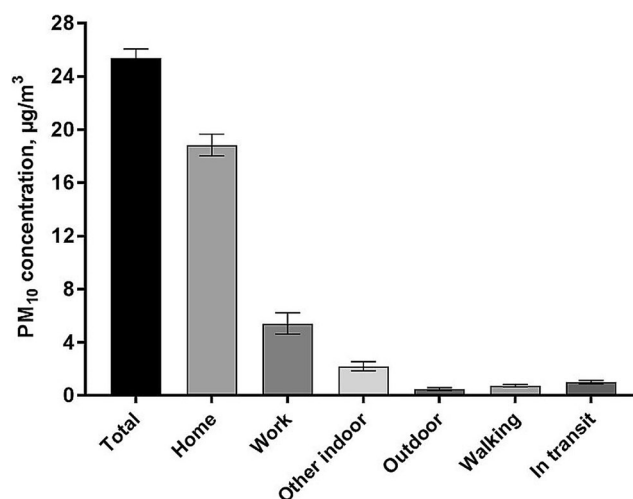


Fig. 6 Personal exposure to PM₁₀ (mean ± SE) in different microenvironments

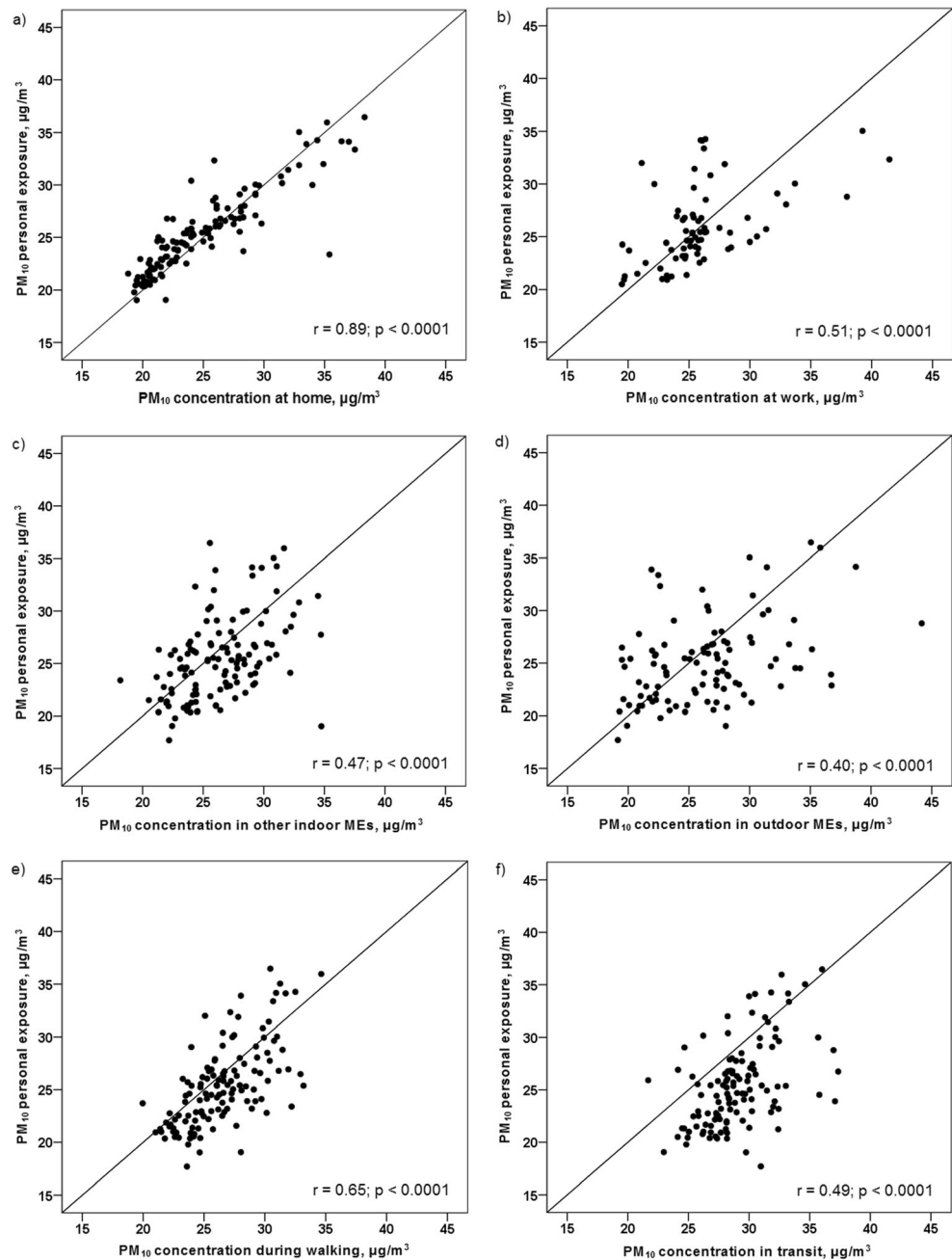
total personal exposure of PM_{10} was received in work ME. Personal exposure in other indoor MEs accounted for 7.6% of the total exposure of PM_{10} . Exposure to PM_{10} in outdoor, walking, and in transit MEs accounted, respectively, for 1.7, 2.8, and 3.5% of total personal PM_{10} exposure.

Similar results have been reported by other authors (de Nazelle et al. 2013; Lonati et al. 2010; Spinazzè et al. 2014). These studies indicated that the largest amount of exposure was received at home. Other indoor locations accounted for about 7% of the total exposure. Personal exposure at work and in travel microenvironments varied more between studies. The differences in personal exposure at work could be due

to occupational differences among the participants of different studies, whereas the differences in travel exposure can be explained by the difference in the distance between home and work and other locations, which results in higher levels of exposure in travel ME.

A correlation analysis between the personal exposure of PM_{10} and the concentration of PM_{10} in different microenvironments was performed by calculating the Pearson correlation coefficient (Fig. 7). A strong positive statistically significant relationship was found between the personal exposure of PM_{10} and home concentration of PM_{10} ($r = 0.89$, $p < 0.0001$). Also, a strong positive statistically significant linear

Fig. 7 Linear relationship between personal exposure of PM_{10} and concentration of PM_{10} in different MEs. **a** Home. **b** Work. **c** Other indoor. **d** Outdoor. **e** Walking. **f** In transit



relationship was found between the personal exposure of PM_{10} and the concentration of PM_{10} during walking ($r = 0.65$, $p < 0.0001$). The correlation coefficient between the personal exposure of PM_{10} and work concentration of PM_{10} was 0.51 ($p < 0.0001$). There was also a moderate relationship between the personal exposure of PM_{10} and the concentration of PM_{10} in other indoor ($r = 0.47$; $p < 0.0001$), outdoor ($r = 0.40$; $p < 0.0001$), and in transit ($r = 0.49$; $p < 0.0001$) MEs.

Similar results were obtained in the study with children conducted by Gulliver and Briggs (2005) in the UK. A strong positive linear relationship ($r = 0.79$) was found between modelled integrated PM_{10} exposure (in home, school, and travel microenvironments) and home exposure.

Improving PM_{10} exposure assessment by applying integrated exposure model

The estimation of air pollution exposure is essential in epidemiological studies seeking to investigate the relationship between air pollution and health effects, and accurate application of exposure assessment methods may significantly improve the results of epidemiological analysis.

In the past studies, exposure to air pollution was assigned based on residence location (Jerrett et al. 2005). However, people exposure varies widely because of their individual daily movement patterns as they move through different microenvironments with varying air pollutant concentrations (Kwan et al. 2015). Recent studies have demonstrated the necessity to consider human activity patterns and spatiotemporal variability of air pollution in exposure and health risk assessment (Park and Kwan 2017).

The smartphone study included randomly selected participants (125 individuals) from the entire Kaunas cohort (1141 individuals) to assess personal exposure to PM_{10} based on time-activity patterns. We performed an individual participant data analysis, which was used to develop the integrated exposure model and to evaluate the exposure of PM_{10} for the entire Kaunas cohort, to assess the association of PM_{10} exposure with the risk of allergies. The integrated model for estimating PM_{10} exposure was developed using a linear regression model. A statistical analysis was carried out to select appropriate indicators with the highest statistically significant impact on PM_{10} exposure estimation model.

The dependent variable was personal exposure of PM_{10} assessed in the smartphone study.

We found that 65% of the total exposure of PM_{10} is received in home ME and these results indicate that home exposure has the largest influence on total personal exposure. These results are similar to those reported previously (de Nazelle et al. 2013; Good et al. 2016). A strong positive statistically significant linear relationship ($r = 0.89$; $p < 0.0001$) was found between the concentration of PM_{10} in home ME and personal exposure

of PM_{10} . Therefore, PM_{10} concentration at home had the largest impact on integrated exposure model.

One of the most important factors for estimating PM_{10} exposure is person's day activities (Karanasiou et al. 2014; Zuurbier et al. 2010). Travel frequency variable was used to create integrated exposure model of PM_{10} .

Other variable was dog ownership, which was encoded and had two values. Taking a dog for a walk in parks or in other green spaces that have a lower level of air pollution has a significant impact on PM_{10} exposure. There is evidence that dog walking is related to the relationship between green space exposure and physical activity change, as it leads to a higher level of physical activity and often occurs in green space (Dalton et al. 2016). Studies have shown that green spaces have an impact in reducing air pollution (Dadvand et al. 2012; Selmi et al. 2016); however, green spaces near intensive traffic can lead to health risks associated with air pollution (Wolch et al. 2014).

The amount of greenness around the residence place was an important indicator and had a statistically significant impact on the integrated exposure model of PM_{10} . Urban vegetation is essential for improving air quality (Janhäll 2015). Studies have indicated that there is a positive relationship between the exposure to greenness and physical activity (James et al. 2015; Lee et al. 2015) as well as more active lifestyle and more frequent walks (van den van den Berg et al. 2015).

Model parameter estimates and p values are presented in Table 2.

The most commonly used model, the linear regression model, was used to assess the integrated PM_{10} exposure. The linear regression model is widely used in air pollution exposure studies (Adam et al. 2015; Korek et al. 2016).

A statistically significant linear regression model was developed ($F(4, 115) = 134.1$; $p < 0.0001$) with a determination coefficient $R^2 = 0.82$. This model was used to assess the integrated exposure of PM_{10} for the entire Kaunas cohort.

A similar study was conducted by Kwan et al. (2015) in Ohio (USA), who assessed static and dynamic exposure to particulate matter by integrating the spatial-temporal variability of PM_{10} with time-activity patterns of individuals and investigated the variation in exposure with respect to people's demographic and socioeconomic

Table 2 Estimates of variables included in the model

Variable	B coefficient	SE	t	p value
Intercept	4.91	1.00	4.91	< 0.0001
PM_{10} concentration at home	0.76	0.03	22.70	< 0.0001
Travel frequency	0.81	0.38	2.11	0.037
Dog ownership	-0.91	0.35	-2.58	0.011
Greenness around residence place	1.33	0.42	3.14	0.002

characteristics. The results showed that there were no significant differences between static and dynamic exposures for all gender, education, income, and age groups. Further statistical analysis showed that dynamic exposure of PM_{10} differed statistically significantly between different income groups, but there was not enough evidence to conclude statistically significant differences in exposure to PM_{10} within different groups of other demographic and socioeconomic factors. A multivariate linear regression analysis was performed to assess the effects of independent variables (such as gender, education, income, and age) on dynamic exposure to PM_{10} . Regression model results showed that independent variables accounted for only about 3% of the individual exposure. These results could be due to the uncertainties in PM_{10} emissions and sources, lack of air quality monitoring stations in the studied area, and not sufficiently accurate data of time-activity travel diaries, because they did not provide information about the actual travel routes taken, and this estimation was based on the assumption of the shortest path between two points, which was applied to all the trips by the study participants.

The relationship between integrated exposure to PM_{10} and the risk of allergies in adults

The distribution of the control group that included non-allergic adults and allergy cases in different zones of PM_{10} pollution in Kaunas city is presented in Fig. 8. The control group and cases were evenly distributed in the city.

One thousand one hundred and forty-one participants of Kaunas cohort were used to assess the association between particulate matter exposure and the risk of allergies in adults. The percentage of individuals with allergic diseases was 8.2% in this study.

The prevalence of allergy cases among adults exposed to the 1st PM_{10} exposure tertile was 5.7%, to the 2nd 9.0%, and to the 3rd PM_{10} exposure tertile 9.9%. Increased PM_{10} exposure tended to increase allergic diseases risk (Table 3).

Crude and adjusted odds ratios (ORs) and their 95% confidence intervals (CI) for allergies by PM_{10} exposure tertiles are presented in Table 3. In crude analyses, the risk of allergies increased statistically significantly with increasing exposure to particulate matter. After adjustment for confounding variables, the OR for the risk of allergies among adults exposed to

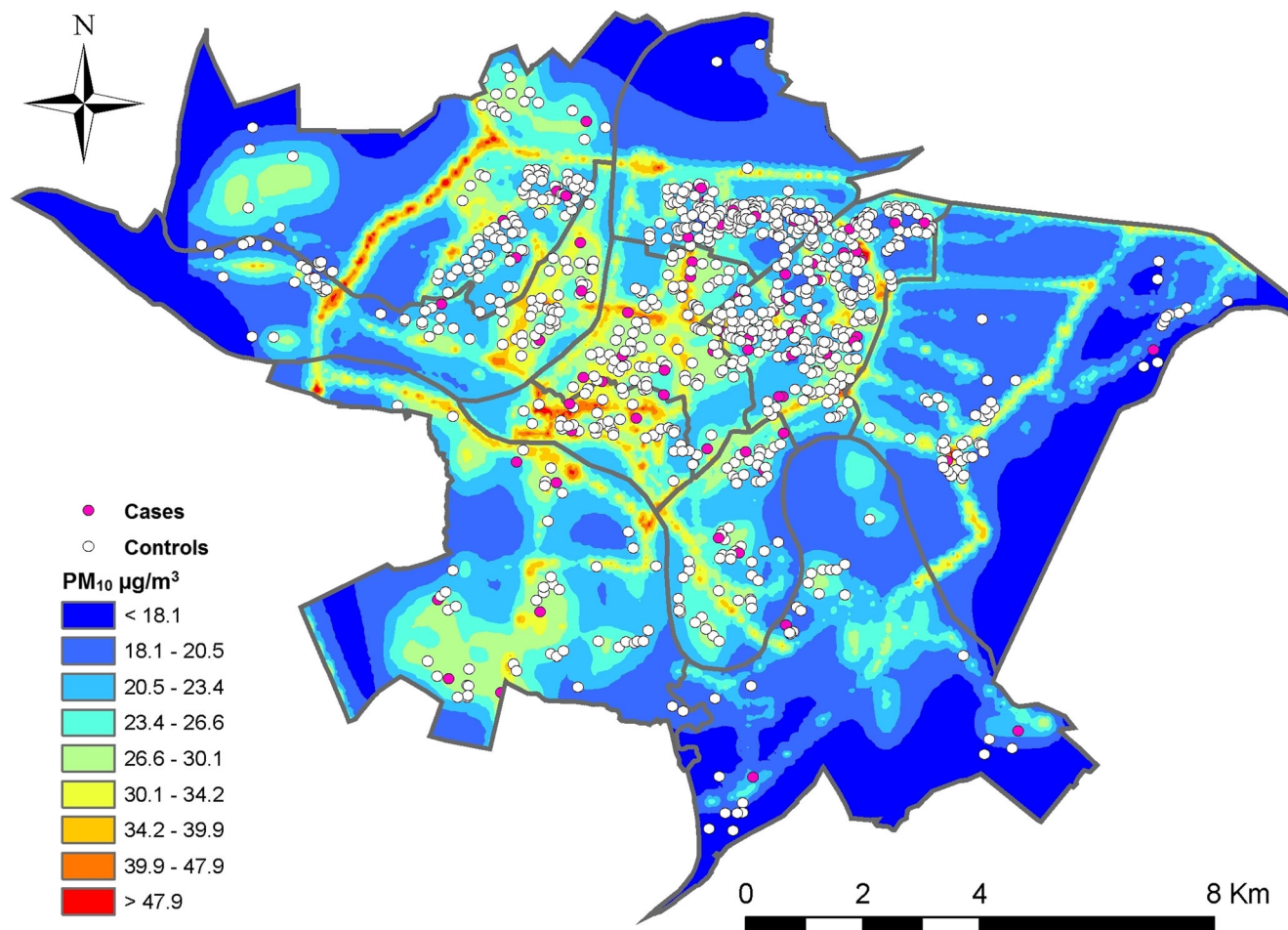


Fig. 8 The dispersion of PM_{10} pollution and the distribution of controls and cases in Kaunas city

Table 3 Crude and adjusted odds ratios (ORs) and their 95% confidence intervals (CI) for allergies by PM₁₀ exposure tertiles and IQR

PM ₁₀ exposure	Cases <i>N</i> (%)	Controls <i>N</i> (%)	Crude OR		Adjusted ¹ OR	
			OR	95% PI	OR	95% PI
1st tertile	21 (5.7)	349 (94.3)	1	Reference	1	Reference
2nd tertile	34 (9.0)	344 (91.0)	1.64	0.94–2.89	1.68	0.92–3.10
3rd tertile	39 (9.9)	354 (90.1)	1.83*	1.06–3.18	2.04*	1.11–3.76
IQR (4.01 µg/m ³)	–	–	1.31*	1.06–1.61	1.29*	1.02–1.62

¹ Adjusted for age, gender, smoking, occupational status, health status, body mass index, impact of physical or emotional health on social activities, and NO₂ exposure

**p* < 0.05

2nd PM₁₀ tertile was 1.68 (95% CI 0.92–3.10) and among adults exposed to 3rd PM₁₀ tertile, it was 2.04 (95% CI 1.11–3.76), compared to the lowest PM₁₀ tertile, and this result was statistically significant.

IQR increase in PM₁₀ (IQR = 4.01 µg/m³) was associated with significantly higher risk of allergies with adjusted OR of 1.29 (95% CI 1.02–1.62).

Our findings suggest that the highest risk of allergies in adults was associated with the highest exposure of PM₁₀. These results are in line with other studies (Agrawal 2012; Künzli et al. 2009). The effect of particulate matter (PM₁₀, PM_{2.5}) exposure on the risk of allergies in children was found by Wang et al. (2016). Morgenstern et al. (2008) found the relationship between air pollution of particulate matter and atopic diseases and increased allergic reactions in children. There are several studies that have indicated the association between traffic-related air pollution including diesel exhaust particles (DEP) and the risk of allergic diseases. The results of these studies showed that DEP exposure may be associated with reduced Th1 function leading to decreased ability to fight respiratory infections and these Th1 cell changes may affect the risk of developing allergic disease (Berger 2000; Schultz et al. 2017). There is evidence that short-term and long-term exposure to particulate matter has been associated with asthma symptoms, poorly controlled asthma, and reductions in lung function in both children and adults (Jacquemin et al. 2012; Malig et al. 2013; Mann et al. 2010; Meng et al. 2010).

This study highlights the importance of considering human time-activity patterns and the complex relations among demographic, social, behavioural, and environmental factors for accurate exposure assessment. The present study has the advantage of using dispersion model, geospatial methods, and mobile tracking and sensing technologies (GPS, accelerometer sensors) that enable a better estimation of personal exposure to particulate matter at an individual level. Another advantage is a large number of characteristics collected by questionnaires that allowed controlling for potential risk factors associated with allergic diseases.

The present study has several limitations that need to be addressed in future research. First, we do not consider the

spatiotemporal variability of the particulate matter in time, as air pollution levels change between days and hours. In this study, we used the annual average PM₁₀ concentration. However, we did not attempt to evaluate the effect of short-term exposure to PM₁₀ on allergies as this study focuses on long-term effect. Second, we assume that indoor air quality is similar to outdoor air quality as it is influenced by the pollutant concentration in the outdoor air, but it may be different because of indoor pollution sources. Third, we do not distinguish different travel modes (car, bicycle, etc.) assuming that each individual uses the same travel mode; however, the identification of different travel modes could improve the accuracy of the results. In addition, allergic diseases such as asthma and allergic rhinitis should be considered separately in further studies, and the questionnaire used to collect information about allergic diseases, symptoms, and the main related factors could be extended. The other limitation of this study is the relatively small sample size that could reduce generalizability to other populations. Additionally, although we observed differences between the main characteristics in two samples and there were no significant differences between the most important ones, the possibility remains that the exposure assessed for the study population does not represent the exposure in the general population and this might not be fully generalizable.

The effects of air pollution on the development or worsening of allergic diseases, especially in adults, using objective measures for exposure assessment have not been widely investigated, and further studies are still needed to better understand of the mechanisms involved in the association between air pollution of particulate matter and allergies and to more accurately examine the contribution of individuals' characteristics to personal exposure to air pollution.

Conclusions

Based on time-activity patterns of 125 participants which were assessed using GPS and accelerometer techniques, individual daily mobility profiles were determined and six MEs were distinguished. Using the data of time-activity patterns, time

spent in different MEs, and the concentration of PM₁₀ of each ME, personal exposure to PM₁₀ was assessed for the study participants. The effect of personal exposure to PM₁₀ on allergy risk in adults was estimated using the approach of integrated exposure models. The study results showed that the lowest average annual concentration of PM₁₀ was determined in home ME, and after using a time-weighted model to assess personal exposure to PM₁₀ for each study participant in different MEs, we have found that home exposure to PM₁₀ accounted for the largest portion of total personal exposure. The results of performance of data analysis at individual-level and the development of integrated exposure models to evaluate the integrated exposure of PM₁₀ for the entire Kaunas cohort suggested that the differences in effects by different estimates of exposure assessment and adjustment for individual factors should be further explored. Our findings showed that the risk of allergies in adults increases with increasing personal exposure to PM₁₀. These findings highlight the importance of reducing PM₁₀ exposure and its effect on allergy risk and considering time-activity patterns, and future research studies are needed to evaluate new exposure assessment methods.

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Compliance with ethical standards

Competing interests The authors declare that they have no competing interests.

Ethics approval Ethics approval was obtained for all aspects of the study by the Lithuanian Bioethics Committee, and informed consent was obtained from all participants.

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