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Validity of self-reported air pollution annoyance to assess long-term exposure to air pollutants in Belgium

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Abstract

 In epidemiological studies, assessment of long term exposure to air pollution is often estimated using air pollution measurements at fixed monitoring stations, and interpolated to the residence of survey participants through Geographical Information Systems (GIS). However, obtaining georeferenced address data from national registries requires a long and cumbersome administrative procedure, since this kind of personal data is protected by privacy regulations. This paper aims to assess whether information collected in health interview surveys, including air pollution annoyance, could be used to build prediction models for assessing individual long term exposure to air pollution, removing the need for data on personal residence address.

 Analyses were carried out based on data from the Belgian Health Interview Survey (BHIS) 2013 linked to GIS-modeled air pollution exposure at the residence place of participants older than 15 years (n= 9347). First, univariate linear regressions were performed to assess the relationship between air pollution annoyance and modelled exposure to each air pollutant. Secondly, a multivariable linear regression was performed for each air pollutant based on a set of variables selected with elastic net cross-validation, including variables related to environmental annoyance, socio-economic and health status of participants. Finally, the performance of the models to classify individuals in three levels of exposure was assessed by means of a confusion matrix.

 Our results suggest a limited validity of self-reported air pollution annoyance as a direct proxy for air pollution exposure and a weak contribution of environmental annoyance variables in prediction models. Models using variables related to the socio-economic status, region, urban level and environmental annoyance allow to predict individual air pollution exposure with a 53 percentage of error ranging from 8% to 18%. Although these models do not provide very accurate predictions in terms of absolute exposure to air pollution, they do allow to classify individuals in groups of relative exposure levels, ranking participants from low over medium to high air pollution exposure. This model represents a rapid assessment tool to identify groups within the BHIS participants undergoing the highest levels of environmental stress.

KEYWORDS

Air pollution, Health Interview Surveys, Exposure assessment, Environmental annoyance

1. Introduction

 The reliability of exposure assessment represents a key component and a challenging issue in the research of the health impact of pollution. Initial epidemiological studies on the adverse effects of environmental pollutants on health traditionally relied on population-level estimates of exposure, through measures collected at fixed monitoring sites (1). Because aggregated data are not always representative of exposure to ambient pollutants at the residence address, an important limitation of these studies was the inaccuracy of personal exposure levels of study participants (2,3). Having an inaccurate estimate of actual exposure can and will reduce the power of the inferences derived from epidemiological studies (4).

 To overcome this problem, air pollution models have been developed worldwide based on geographical analysis and a combination of satellite-derived, meteorological, and land-cover data, 71 to estimate the level of air pollution exposure with high spatiotemporal accuracy $(5-7)$ at any given location. Different statistical methods - ranging from simple linear regression models to more complex machine learning techniques - were used to produce accurate predictions at locations where measurements were not available (8). Other approaches have also recently been developed to allow the assessment of individual exposure to air pollution, such as personal monitoring (9,10). This has the advantage of accurately assessing short-term exposure to air pollution but it cannot be implemented in retrospective or large-scale studies, nor over longer time periods.

 Although more complex air quality models have the ability to improve the spatiotemporal resolution of exposure estimates, they may be data intensive, leading to a limited number of epidemiological studies applying these methods (4). To obtain the interpolated air pollution estimates at the residence, researchers need the exact coordinates of the place of residence of the survey participants. This implies the processing of personal data and might generate long and cumbersome administrative procedures.

 The question then arises if anonymous data collected in health interview surveys, such as self- reported air pollution annoyance, could be used to build prediction models for assessing individual long term exposure to air pollution. If valid, this approach could represent a rapid and inexpens iv e 87 exposure assessment tool applicable on fully anonymous data, that does not require geolocalizing study participants' home addresses.

 The relationship between exposure to air pollution and annoyance is however not straightforward. Air pollution annoyance has been proposed as an indicator to assess long term exposure to air 91 pollution $(11-14)$. In these studies, it has been suggested to use population average scores, and not individual scores, for grading air quality within areas since several studies showed that individual factors, other than the actual level of exposure, may influence air pollution perception an d that those variations may be levelled out on a population level scale (15). Beyond the environment in which people live, social and psychological factors play an important role in air pollution perception (16–18).

 The association between an individual's air pollution exposure and perception of air quality thus 98 remains unclear (19–23). Whereas several studies have examined to what extent self-reported air pollution annoyance could be used as a proxy to assess ambient air pollution exposure, to date no studies have explored the possibility to valorize other self-reported variables collected in population surveys to assess individual long term exposure to air pollution. In the latter, air pollution exposure has been associated with several factors such as health status, socio-economic status and urban level; those factors could have a higher predictive power compared to air pollution annoyance to assess individual air pollution exposure (24,25).

 The objective of this paper is therefore threefold: 1) to assess the validity of air pollution annoyance as a proxy for individual long-term exposure to air pollution; 2) to explore the potential use of self- reported information on individual respondent's characteristics collected in population surveys (including environmental annoyance, health status and socio-economic status) to predict individual long-term exposure to air pollution; and 3) to assess the relative added value of environmental annoyance indicators in prediction models compared to other individual characteristics.

- **2. Materials and methods**
- Study area

 The study area is the whole of Belgium, a small country situated in Western Europe. The country is divided in three regions: the Brussels Capital Region, the Flemish Region and the Walloon 116 Region. Belgium has a surface area of 30,688 km² and a population of 11.5 million inhabitants (in 2013).

Study population and data

 Data were extracted from the Belgian Health Interview Survey (BHIS) conducted in 2013. The BHIS is a national cross-sectional epidemiological survey carried out every five years by Sciensano, the Belgian Institute for Health, in partnership with Statbel, the Belgian statistical office. A stratified multistage, clustered sampling of the population was used. The survey covers socio-demographic characteristics, physical and mental health status, environmental annoyance and lifestyle (26).

 Only participants older than 15 years, who completed the entire set of questions, were included in the analysis. This represented 6497 participants or 71% of the initial sample. The dataset was further enriched with objective measures of air pollution exposure, based on the geographical coordinates of the residential address of participants and processed using GIS. This data linkage at the individual level was done in partnership with Statbel, the national statistical institutes of Belgium. An application to the Sector Committee Statistics has been submitted and approved (see 131 Decision STAT n°02/2018 on 19/01/2018).

132 Objective measurements of the environment

Air pollution

 The annual average concentrations in 2013 (the year of BHIS participation) of particulate matters (*PM2.5, PM10),* black carbon *(BC)*, Ozone (*O3*) and nitrogen dioxide (*NO2*) at the participant's residence address were used as indicators of air quality. Exposure at the residential address of participants was obtained through the national monitoring system supervised by the Belgian interregional environment agency (IRCEL – CELINE). Concentrations of pollutants are assessed on a daily basis through a dense network of stations distributed all over the country. Residential 140 exposure (μ g/m³) to *PM*, *BC* and *NO*₂ at the participants' residence was modelled at high resolution using a spatiotemporal interpolation model (27). This model included air pollution data from the Belgian fixed monitoring stations and CORINE Land Cover (CLC) information obtained by 143 satellites in combination with a dispersion model including point and line sources (27–29). The overall model performance was assessed by leave-one-out cross-validation and was based on 34 monitoring points for *PM2.5*, 44 for *NO2* and 14 for *BC*. Out of all spatial and temporal variability, the model explained 78% for *NO2* (30), 80% for *PM2.5* (30), and 74% for *BC* (31). In addition, accuracy of the model to assess individual exposure was demonstrated in a study comparing

- modelled *PM2.5* and *BC* at the address of residence with internal exposure measured in urine (32).
- All air pollution indicators were used as continuous variables. Maps of air pollution exposure
- (*PM2.5* and *BC*) in Belgium are available in the appendices (**Fig A. 1.** and **Fig A. 2**.)

Regional and urban level

- We used the urbanization level as it was defined in the BHIS: urban, suburban and rural level.
- The degree of urbanization was determined by morphological and functional characteristics of
- municipalities (full methodology described in 27) derived from census data. Brussels and other
- cities are grouped in the category "urban" (33,34).

Self-reported participant characteristics

Environmental annoyance

 The participants' environmental annoyance was assessed at three different geographical levels: in the neighborhood, at the residence address (outdoors) and in the dwelling (indoors). The variables

are listed in **Table 1**.

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 The degree of annoyance in the neighbourhood and in the dwelling was assessed through a four- point Likert scale (not at all a problem, minor problem, fairly big problem, very big problem). A five-point Likert scale (not at all a problem, slightly, moderately, very, extremely) was used to grade the level of annoyance at home. The degree of annoyance in the dwelling was assessed through a four-point Likert scale (not at all a problem, minor problem, fairly big problem, very big problem).

170 **Indicators of socio-economic status**

171 To describe participants' socio-economic status, we used the following indicators: "*age",*

172 *"gender", "household composition*" (single with no children, single parent with child(ren), couple

173 without child(ren), couple with child(ren), unknown)*, "highest educational level in the household"*

 (no diploma or primary education, lower secondary, higher secondary, higher)*, "country of birth"* (Belgian, non-Belgian-EU, non-Belgian non-EU)*, "civil status"* (single, married or legally cohabitant, widow(er) and not remarried, divorced and not remarried), *"reported household income", "unemployment status"* (yes vs no), *"housing tenure*" (owner, renter from a social housing association or living rent free, renter from an individual private landlord), *"type of dwelling"*(apartment or flat in a building with ten or more dwellings, apartment or flat in a buildin g with three to nine dwellings, apartment or flat in a building with two dwellings, residential home for the elderly/instit ution for the elderly, room or furnished studio/others, semi-detached house, terraced house, detached house), and *"ability to make ends meet with the household income* (easily, rather easily, rather hard, hard, very hard).

Indicators related to health status

 We used the following binary indicators: chronic/handicap condition, asthma, depression, chronic lung disease, allergies, cardiovascular disease, high blood pressure and diabetes. For each disease, the information was obtained through the following question: "In the last 12 months, did you suffer 188 from...". In addition, ordinal variables were used to describe the number of chronic diseases (0,1,2,>3) and the body mass index (BMI) (underweight (< 18.5), normal (18.5-24.9), overweight $(25-29.9)$, obese (≥ 30)).

Statistical analyses

 The optimal transformation to obtain normality was applied for variables related to air pollution exposure. The *NO2* exposure was transformed on the squared root scale and *BC* on the inverse scale. *PM2.5* and *PM10* were used on the normal scale. Data included in the analysis were complete-cases (n=6497).

 Univariate linear regressions were performed to assess the relationship between air pollution annoyance and the modelled exposure to each air pollutant individually. Univariate linear regressions were also performed between each selected BHIS variable and each air pollutant exposure.

 A multivariable linear regression was performed for each air pollutant based on a set of variables selected with elastic net cross-validation (35), among which BHIS variables related to environmental annoyance, socio-economic status, geographical region and health status of participants.

 The sample was randomly separated in a training (70%) and a test dataset (30%). To assess the accuracy of each predictive model, three statistics were computed: 1) the R-squared; 2) the root mean squared error (RMSE), which represents the average distance of the observed y values from the estimated Y values; and 3) the coefficient of variation, calculated by dividing the RMSE by 208 the mean of the air pollution exposure.

 Based on the predicted and actual values of air pollution exposure, the accuracy of the predictive models to classify participants in three groups of exposure (based on the tertiles of the actual exposure) was assessed by means of a confusion matrix. A confusion matrix is a specific table layout that allows visualization of the performance of an algorithm where each row represents the instances in an actual class and each column represents the instances in a predicted class, or vice versa. The Kappa coefficient was used to assess the degree of agreement between the two classification groups, taking into account the agreement by chance.

 Sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) were calculated for each model.

 In order to assess the added value of environmental annoyance to predict air pollution, additional predictive models were built: 1) once excluding variables related to the environmental annoyance in the elastic net; and 2) once including only variables related to the environmental annoyance in the elastic net. Parameters of accuracy of each air pollutant model were compared in the three set- ups. Additionally, interactions were tested between each variable related to environmental 223 annoyance and the region.

 Correct estimates were obtained by taking into account the survey weights, strata and clusters relative to the sample design. All analyses were performed using the statistical software R, version 3.6.3 (R Development Core Team 2006).

3. Results

Data description

 In 2013, 25% of the Belgian residents declared to be annoyed by at least one environmental nuisance in the neighborhood, 27% by a nuisance at home and 12% by a problem related to the dwelling. Among the nuisance at home, air pollution annoyance affected 16% of the Belgian citizens (from slightly to extremely).

The medians of the annual mean exposure to *PM2.5*, *PM10*, *NO²* and *BC* were respectively

- 14.74 μg/m³ (95% CI: 13.56-16.94), 21.29 μg/m³ (95% CI: 19.54-23.77), 21.48 μg/m³ (95% CI:
- 236 16.48-30.53) and 1.35 μ g/m³ (95% CI: 1.12-1.83).

 Summary statistics of all the variables considered in the analysis are displayed in the appendices (**Table A. 1.)**

Validity of air pollution annoyance to assess long-term exposure to air

pollution

 The distribution of air pollution exposure according to the level of air pollution annoyance is displayed in **Fig 1**. There is a slight gradient in the median exposure along the levels of annoyance. Surprisingly, the individuals reporting to be extremely annoyed did not have the highest median 245 exposure of $PM_{2.5}$ and PM_{10} . Trends are equal for BC and NO_2 but less noticeable.

Fig 1. Distribution of air pollution exposure according to the level of air pollution annoyance

 (NO2: Nitrogen dioxide, BC: Black Carbon, PM2.5: Particulate Matter <2.5 µm, PM10: Particulate 249 Matter $\leq 10 \text{ µm}$

 In univariate regressions, the proportion of the variability of the air pollution annoyance that could be predicted by the objective exposure to air pollution varied between 2% (for *PM2.5*) and 5% for 253 (NO_2) .

254 The most important contributors to air pollution exposure are the region (\mathbb{R}^2 varies between 39%) 255 for PM_{10} and 63% for $PM_{2.5}$), urbanity (R^2 varies between 33% for $PM_{2.5}$ and 56% for NO_2), the type of dwelling (R² varies between 25% for $PM_{2.5}$ and 35% for NO_2), and the country of birth (R² 257 varies between 5% for $PM_{2.5}$ and 15% for NO_2).

258 The \mathbb{R}^2 of the univariate regressions between $PM_{2.5}$ exposure and each selected BHIS variable related to environmental annoyance, socio-economic status, health status and geographical location are displayed in **Fig 2**. Coefficients of all univariate regressions for *PM2.5, PM10, NO2* and *BC* are available in the appendices (**Tab A. 2**, **Tab A. 3** and **Tab A. 4).**

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 $\frac{264}{265}$

Fig 2. Proportion of the variability of PM_{2.5} exposure predicted by each selected Belgian Health Interview Survey variable (pb =problem)

- Use of self-reported information on individual characteristics to predict
- individual long-term exposure to air pollution
- In multivariable analysis, the set of BHIS variables selected by the elastic net cross-validation is
- essentially the same for the *PM2.5, PM10* and *NO2* models. For *BC*, environmental variables retained
- in the model are predominantly related to road traffic annoyance. Coefficients of the multivariable
- regression models are displayed in **Table 2**.

Table 2. Coefficients of the multivariable regression models for each air pollutant

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277 $* <0.05** <0.01*** <0.001$. Results must be considered by column

 The proportion of the variability of the air pollution exposure explained by the predictive models vary between 60% (for *PM10*) and 75% (for *PM2.5* and *NO2*). The performance of the predictive models is good and is visualized in the plots of the predicted versus actual values of air pollution exposure (**Fig 3**.). Observations are well distributed around the lines, indicating a high level of agreement between predicted and actual values. Prediction errors (coefficient of variation) vary between 8% for *PM2.5* and 18% for *BC*. Models tend to slightly overestimate the exposure for the least exposed respondents. We observe that most of the Belgian residents are exposed to *PM2.5*

levels above the WHO exposure guideline.

287
288 **Fig 3**. Predictive versus actual values of the multivariable regression models of air pollution 289 exposure. A : PM2.5, B : PM10, C : NO2, D : BC. Variables included were selected by elastic-net cross validation. All models include housing tenure, region, country of birth, accumulation of rubbish, noise from 291 all sources and vandalism. Models A,B,C include lack of access to parks, noise from train traffic, noise
292 from airplane, able to make ends meet with available household income, noise from neighbors, vibrations, 292 from airplane, able to make ends meet with available household income, noise from neighbors, vibrations,
293 kind of dwelling. Socio-economic status is included in model A and C. Traffic volume and noise from road kind of dwelling. Socio-economic status is included in model A and C. Traffic volume and noise from road traffic are included in model D.

The performance of the model to classify individuals in three levels of exposure, based on the

tertiles of the actual values of exposure, is illustrated by the means of confusion matrix in **Fig 4**.

The prediction accuracy of the models varied between 70% (for *BC*) and 76% (for *PM2.5*) and the

- Kappa coefficient between 0.55 (for *BC*) and 0.64 (for *NO2*) showing a fair to good agreement
- between the two classif ication groups.
- Values of the validity parameters indicated a higher performance of the models to detect highly
- exposed respondents (included in the third tertile).

 I

Fig 4. Confusion matrix and parameters of accuracy for each air pollutant model

Without envi. annoyance All variables Only envi. annoyance $\overline{74}$ 73 72 72 66 66 60 $60 -$ 58 Model Percentage **PM2.5** 40 **PM10** NO₂ **BC** 28 23 $\overline{22}$ $20 -$ 18 18 18 18 15 14 10 10 $\mathbf{9}$ \mathbf{B} $0 \overset{\centerdot}{\text{cv}}$ $R₂$ $\overset{\text{I}}{\text{CV}}$ $\overset{\centerdot}{\text{cv}}$ $R₂$ $R₂$ Coef 309

307 Added value of variables related to environmental annoyance in prediction

308 models

 In **Fig 5**., the parameters of model accuracy of each air pollutant model are compared in different set-ups: 1) with all selected BHIS variables, 2) excluding the variables related to environmental annoyance, 3) with only the variables related to environmental annoyance included in the elastic net. Models 1) and 2) show similar levels of performance in terms of prediction error (CV) and 318 coefficient of determination (R^2) . By contrast, the model including only variables related to environmental annoyance is much less performant.

 Fig 6. Models accuracy to detect three levels of air pollution exposure: prediction accuracy and Kappa coefficient for all air pollutant three models: 1) Model including all variables 2) Model excluding environmental variables 3) Model with only environmental variables.

In **Fig 6.,** the performance of each air pollutant model to classify individuals in three levels of

exposure are compared in each set-up.

4. Discussion

Main findings

 We investigated the associations between environmental annoyance and individual characteristics and their related objective measure of air pollution (*PM2.5, PM10, BC*, *O³ NO2*). In Belgium, a considerable proportion (16 %) of residents reported to be annoyed by air pollution. Although participants were more likely to be annoyed when air pollution concentrations were higher, data on air pollution annoyance was only weakly associated with individual air pollution exposure. Air pollution annoyance represents therefore a poor indicator of air pollution exposure.

 Our results suggested that other self-reported individual characteristics from health interview surveys can be used to build prediction models to assess individual air pollution exposure. We demonstrate that models containing variables related to socio-economic status, region, urban level and environmental annoyance allowed to predict the measured air pollution exposure of the BHIS participants with a percentage of error ranging from 8% to 18%. Although these models do not provide a very accurate prediction, they do allow to classify individuals in groups of relative exposure levels (e.g. low, medium, or high exposure). Survey participants who are exposed to high air pollution levels might constitute a high risk group in terms of public health.

 Indeed, a pilot project on the environmental burden of disease in Europe showed that among the environmental stressors, air pollution had the highest public health impact, followed by second- hand smoke and traffic noise (36), and that about 5% of the myocardial infarctions can be triggered by air pollution exposure (37). Exposure to air pollution can cause a variety of adverse health outcomes such as respiratory infections, lung cancer, heart disease and mental disorders (38,39).

 It has to be noted that our models are only valid for the Belgian population. Because the models are essentially relying on regional and socio-economic features and due to the limited contribution of the variables related to environmental annoyance, models are roughly transposable over long periods of time and will not be able to reflect an air pollution change over time.

 Nevertheless, the limited contribution of the variables related to the environmental annoyance in the air pollution prediction models does not necessarily make them irrelevant in health interview surveys. In fact, the perception of high air pollution may often be more deleterious to well-being and quality of life than the air pollution itself (40–43). Annoyance may indeed be considered as a stressor causing stress-related diseases (44,45). Although self-reported annoyance is not a good proxy for exposure, this indicator remains a useful complementary tool for health surveillance. Air pollution annoyance represents a key factor in public acceptance of environmental policy measures. The perception of air pollution and its health impact supports public understanding of the importance of environmental policies and increases their acceptability (46–48). Improving people's perception of air pollution can thus increase the chances of success of preventive measures (18).

 Other important findings from our study are that people can be very and even extremely annoyed by air pollution at exposure levels that lie below the current European Union (EU) air pollution quality guidelines values. This is in accordance with several previous European studies, emphasizing the need to reduce air pollution levels even further (44,49).

 The weak association found between individual air pollution annoyance and modelled exposure to air pollutants at the residence is consistent with findings reported in other studies (11,14,18,20,22,49–53). By examining the factors related to air pollution annoyance in six European countries, Rotko et al. found no association between *NO2* exposure level and individual annoyance scores (16). Forsberg et al. reached the same conclusion by looking at the association between individual exposure to sulfur dioxide (*SO2*) and self-reported annoyance (54). In the UK, Williams and Bird reported that the perception of air pollution exposure was not associated with air quality data for urban areas (55). By contrast, several studies have shown that at the population level the mean annoyance was more strongly associated with central measurements of air pollution $(11-14,16,22,43)$.

 The low or neutral relationship at the individual level can be explained by the fact that people's perception of air quality is socially and cultural constructed (56–59). Annoyance can be modified both by personal factors such as age, gender, level of education and health status or by community level factors such as attitudes toward the exposure source (11,13,14,17–20,54,57,60–63). The weak association could also partially be explained by the fact that people highly annoyed by air pollution may choose to live further away from traffic and polluted areas.

 In our study, the variability of air pollution exposure that was explained by the annoyance scale was slightly higher for *NO2* compared to the other pollutants. This suggest that participants were mainly annoyed by environmental factors related to traffic which is consistent with the results reported in other European studies (64,65).

Strengths and limitations

Future studies might address some of the limitations of this study.

392 Firstly, the limited range of the annoyance scale used in our study (five points-scale) is maybe not sufficient to grasp the variability of the perception related to air pollution exposure. In other studies, a 10 or 11-points scale was used (11,13,49). Secondly, in our study the validity of the air pollution annoyance indicator was only tested at the individual level. The association between self reported annoyance and air pollution exposure might have been stronger at the population level $\frac{1}{2}97$ (such as the city level), as has been shown in previous studies (11,66). Thirdly, the use of annual mean estimates of particulate matter to estimate the association between air pollution exposure and annoyance should be questioned and may not be the most appropriate parameter. Indeed, in psychometric research the *peak-end rule* suggests that people tend to recall events by their highest point of intensity or how they end (67). The reason for this may be that human memory is biased 402 toward extremes and not central tendencies. Further research might assess the accuracy of a peak- hour air pollution model compared to an annual average model. In addition, there are other air pollutants such as organic compounds, sulfur dioxide and carbon monoxide that we did not take into account and which might be reflected by air pollution annoyance. Finally, an important condition we were not able to take into account is the daily mobility of the participants, implying that residential exposure might not contribute most to personal exposure. For example, participants who work close to their home are more likely to have an accurate exposure assessment compared to those who work elsewhere (68).

 The main strength of this study lies in the novelty of the approach used to assess the validity of self-reported air pollution annoyance. While past studies have examined the determinants of air pollution annoyance above the accurate air pollution exposure, this research explored the potential use of the air pollution annoyance indicator to predict the objective individual air pollution exposure. Furthermore, this is the first study to explore the possibility to valorize and utilize other self-reported variables collected in population surveys to assess individual long term exposure to air pollution.

 Even if prediction models based on survey data do not represent a very accurate exposure assessment tool at the individual level, they have the advantage to allow a classification of the individuals in three levels of air pollution exposure with a good accuracy. The model specifically developed in this paper represents a quick and easy tool to select the most exposed groups, which would benefit most from environmental change in Belgium. Further analysis would be needed to validate these prediction models in the following BHIS waves.

5. Conclusions

 The aim of this study was to assess the validity of air pollution annoyance, a questionnaire-based indicator, as a proxy for individual long-term exposure to air pollution and to explore the potential use of self-reported information on individual characteristics collected in population surveys to improve the prediction of individual exposure to air pollution. Our results suggest a limited validit y of self-reported air pollut ion annoyance for assessing air pollution exposure direct ly and a weak contribution of environmental annoyance variables in prediction models. Other individual characteristics related to the socio-economic status and variables related to the urban level and regions appear to have a higher predictive power in the model.

Appendices

436 **Fig A.1.** Air pollution exposure in Belgium with regional boundaries indicated. Annual mean (2013) of BC 437 (μ g/m³). $(\mu$ g/m³).

⁴⁴⁸ **Fig A.2.** Air pollution exposure in Belgium with regional boundaries indicated. Annual mean (2013) of $P M_{2.5} (\mu g/m^3)$. $PM_{2.5} (μg/m³).$

454 **Tab A1.** Description of the sample population

 $\begin{array}{c} \hline \end{array}$

	PM2.5 (natural scale)		PM10 (natural scale)		NO ₂ (squared root scale)		BC (inverse scale)	
		R2/ MSP		R2/ MSP		R2/M		
Environme ntal	coefficient	E/R MSP E/	coefficient	E/R MSP E/	coefficient	SPE/ RMSP E/	Coefficient	R ₂ /MSP E/RMS
annoyance	$[95\%$ CI]	CV	$[95\%$ CI]	CV	[95% CI]	CV	$[95\% \text{ CI}]$	PE/CV
Neighborh		0.02/		0.01/ 12.29		0.05/0		
ood: at least one	$0.53***$	5.9/ 2.4/0.	$0.63***$	13.56	$0.36***$.86/ 0.92/0	$-0.07***$	0.03/0.0 5/0.23/0
condition	[0.37; 0.69]	16	[0.35;0.9]	/0.17	[0.29; 0.44]	.19	$[-0.06; -0.08]$.31
		0.01/		0.02/		0.02/0		
Lack of access to		6/ 2.4/0.		11.3/ 3.36/		.86/ 0.94/0		0.03/0.0 5/0.23/0
parks		16		0.16		.20		.31
Minor								
problem (vs not at	$0.41**$		$0.88***$		$0.26***$		$-0.04*$	
all)	[0.11; 0.71]		[0.38; 1.38]		[0.11; 0.4]		$[-0.08;0]$	
	$0.67***$		$0.9**$		$0.42***$		$-0.09***$	
Fairly big	[0.31;1.02]		[0.32;1.48]		[0.24;0.6]		$[-0.13; -0.05]$	
	$0.81**$		$0.96**$		$0.59***$		$-0.09**$	
Very big	[0.3;1.33]		[0.26;1.65]		[0.37; 0.82]		$[-0.16; -0.02]$	
		0.08/		0.06/		0.11/0		
		5.6/ 2.3/0.		11/ 3/0.1		.75/ 0.86/0		0.09/0.0 5/0.22/0
Rubbish		16		6		.18		\cdot 3
Minor								
problem	$0.8***$		$1.35***$		$0.37***$		$-0.09***$	
(vs not at all)	[0.54;1.06]		[0.96; 1.73]		[0.26; 0.49]		$[-0.12; -0.06]$	
	$1.48***$		$2.22***$		$0.78***$		$-0.18***$	
Fairly big	[1.15;1.82]		[1.65; 2.78]		[0.66; 0.91]		$[-0.21; -0.15]$	
	$1.99***$		$2.62***$		$1.1***$		$-0.25***$	
Very big	[1.44; 2.54]		[1.92; 3.32]		[0.93;1.27]		$[-0.3; -0.2]$	
		0.06/		0.06/		0.12/0		
		5.7/ 2.4/0.		11.6/		.75/ 0.87/0		0.1/0.05
Vandalism		16		3.4/0. 16		$.18$		0.22/0.3
Minor								
problem								
(vs not at	$0.73***$ [0.5;0.96]		$1.32***$		$0.47***$		$-0.09***$	
all)	$1.42***$		[0.97; 1.68] $1.8***$		[0.36; 0.58] $0.79***$		$[-0.12; -0.07]$ $-0.17***$	
Fairly big	[1.1;1.73]		[1.36; 2.23]		[0.66; 0.91]		$[-0.2; -0.14]$	
	$1.89***$		2.88***		$0.98***$		$-0.23***$	
Very big	[1.31;2.46]		[2.02; 3.73]		[0.77;1.2]		$[-0.28; -0.18]$	

456 **Tab A2.** Univariate regressions between air pollution and each selected BHIS variable related 457 environmental annoyance

458 *<0.05 **0.01 ***0.001

459 **Tab A.3.**Univariate regressions between air pollution and each selected BHIS variable related to 460 the socio-economic status

	PM2.5 (natural				NO ₂ squared root				
	scale)			PM10 (natural scale)		scale)		BC (inverse scale)	
		R2/		R2/					
		MSP		MSP		R2/M			
		E/R		E/R		SPE/R		R ₂ /M _{SP}	
	coefficient	MSP	coefficient	MSP	coefficient	MSPE	coefficient	E/RMS	
	$[95\% \text{ CI}]$	E/CV	$[95\% \text{ CI}]$	E/CV	$[95\% \text{ CI}]$	/CV	[95% CI]	PE/CV	
		0.001				0.01/0			
		/6.08		0.001		.89/0.	$0.0006*$	0.008/0.	
	Ω	/2.46	-0.01	/11.4	θ	94/0.2	$[-0.00007; -]$	05/0.23/	
Age	$-0.01;0$	/0.16	$[-0.01;0]$	5/3.3	[0;0]	Ω	0.000005	0.31	

463 health status and geographical location

465 **Credit authorship contribution statement**

466 **Ingrid Pelgrims:** Methodology, Formal analysis, Visualization, Writing - Original Draft. **Brecht**

467 **Devleesschauwer:** Conceptualization, Supervision, Project administration, Funding acquisition,

468 Writing - Review & Editing. **Hans Keune:** Project administration, Writing - Review & Editing.

469 **Tim S. Nawrot:** Resources, Writing - Review & Editing. **Roy Remmen:** Conceptualization,

470 Writing - Review & Editing. **Nelly D. Saenen:** Resources; Writing - Review & Editing. **Isabelle**

471 **Thomas:** Writing - Review & Editing. **Vanessa Gorasso:** Writing - Review & Editing. **Johan**

472 **Van der Heyden:** Resources, Writing - Review & Editing. **Delphine De Smedt:** Writing -

473 Review & Editing

474 **Eva M De Clercq:** Conceptualization, Supervision, Visualization , Writing - Review & Editing

Declaration of competing interest

- The authors declare that they have no known competing financial interests or personal
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