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Modeled and perceived RF-EMF, noise and air pollution and symptoms in a population cohort. Is perception key in predicting symptoms?

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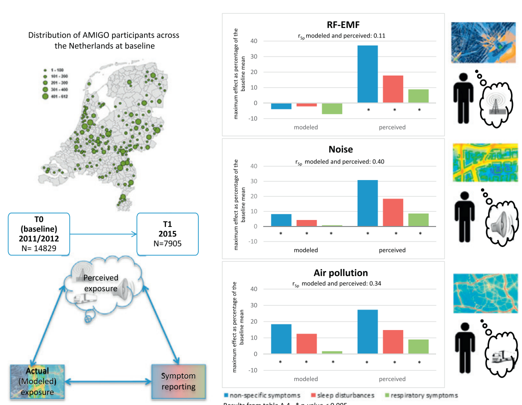
HIGHLIGHTS

- We studied RF-EMF, traffic noise and air pollution in a general population cohort.
- Perceived and modeled exposures were associated with symptoms except modeled EMF.
- Modeled exposures effects were attenuated upon adjustment for perceived exposures.
- Risk assessment may be biased unless modeled and perceived exposures are considered.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Psychosocial research has shown that perceived exposure can influence symptom reporting, regardless of actual exposure. The impact of this phenomenon on the interpretation of results from epidemiological research on environmental determinants of symptoms is unclear.
Objective: Our aim was to compare associations between modeled exposures, the perceived level of these exposures and reported symptoms (non-specific symptoms, sleep disturbances, and respiratory symptoms) for three different environmental exposures (radiofrequency electromagnetic fields (RF-EMF), noise, and air pollution). These environmental exposures vary in the degree to which they can be sensorially observed.
Methods: Participant characteristics, perceived exposures, and self-reported health were assessed with a baseline (n = 14,829, 2011/2012) and follow-up (n = 7905, 2015) questionnaire in the Dutch population-based

Abbreviations: AMIGO, Occupational and Environmental Health Cohort Study; 4DSQ-S, somatization scale of the Four-Dimensional Symptom Questionnaire; ESCAPE, European Study of Cohorts for Air Pollution Effects; MOS, Medical Outcomes Study; STAMINA, Standard Model Instrumentation for Noise Assessments.

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Noise (traffic)
Air pollutants (traffic);perceived exposure
Symptom reporting
Multidisciplinary longitudinal cohort study

Occupational and Environmental Health Cohort (AMIGO). Environmental exposures were estimated at the home address using spatial models. Cross-sectional and longitudinal regression models were used to examine the associations between modeled and perceived exposures, and reported symptoms.

Results: The extent to which exposure sources could be observed by participants likely influenced correlations between modeled and perceived exposure as correlations were moderate for air pollution ($r_{Sp} = 0.34$) and noise ($r_{Sp} = 0.40$), but less so for RF-EMF ($r_{Sp} = 0.11$). Perceived exposures were consistently associated with increased symptom scores (respiratory, sleep, non-specific). Modeled exposures, except RF-EMF, were associated with increased symptom scores, but these associations disappeared or strongly diminished when accounted for perceived exposure in the analyses.

Discussion: Perceived exposure has an important role in symptom reporting. When environmental determinants of symptoms are studied without acknowledging the potential role of both modeled and perceived exposures, there is a risk of bias in health risk assessment. However, the etiological role of exposure perceptions in relation to symptom reporting requires further research.

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1. Introduction

Radiofrequency electromagnetic fields (RF-EMF) from mobile phone base stations, noise exposure from road traffic, and air pollutants are environmental exposures often clustered in more densely populated area (Allen et al., 2009; Davies et al., 2009). The general population is involuntarily exposed to these exposures, and many people have concerns about potential health risks. Recent studies have highlighted a complex interplay between these environmental exposures, perceptions of exposure and health risks, and symptom reporting (Claeson et al., 2013; Héritier et al., 2014; Martens et al., 2017). For example, for residential RF-EMF exposure from mobile phone base stations we recently showed, using a longitudinal design, that perceived, but not modeled exposure, was associated with self-reported symptoms (Martens et al., 2017). For noise from road traffic and air pollutants, perceptions mediated the effect of exposure on symptoms (Claeson et al., 2013; Héritier et al., 2014). These studies show that research into environmental determinants of symptoms can benefit from applying insights from both psychosocial and epidemiological research disciplines.

The current study compares effects of RF-EMF from mobile phone base stations, noise and air pollutants from road traffic for the following symptom-based health outcomes: non-specific symptoms, sleep disturbance, and respiratory symptoms. These health outcomes are chosen based on variation in the plausibility of the link with the different environmental exposures. For environmental RF-EMF exposure, there is evidence of changes in sleep electroencephalography (EEG) (Regel et al., 2007), but no convincing epidemiological evidence for specific effects on symptoms, nor a known biological mechanism (Baliatsas et al., 2012; Röösli et al., 2010). However, people who regard themselves as electrohypersensitive report a wide variety of non-specific symptoms, such as headache, fatigue, and pain which they attribute to EMF exposure (Dieudonné, 2016; Hagström et al., 2013). Noise exposure on the other hand, can induce arousal, which can be observed during sleep through changes in EEG, heart rate, and respiration (Joseph, 2009). Prior epidemiological studies reported associations between noise exposure and sleep disturbances e.g., (Muzet, 2007; Öhrström, 1989; Pirrera et al., 2010), and there is also evidence for effects on wellbeing and overall symptoms (Laszlo et al., 2012). Air pollutants can cause oxidative stress and an inflammatory response (Kelly, 2003). Epidemiological studies have found associations between exposure to air pollutants and respiratory symptoms such as shortness of breath, coughing, and wheezing (Mar et al., 2004; Modig and Forsberg, 2007; Patel et al., 2010).

The expectation that negative health effects may occur, can itself induce symptoms when people think they are exposed, regardless of the actual exposure and risk (Crichton et al., 2014; Szemerszky et al., 2010; Witthöft and Rubin, 2013). This is also described as nocebo-effect, as the counterpart of placebo (Hahn, 1997). Nocebo-effects may be part of a circular process, where experiencing symptoms can also influence perceptions of potential environmental health hazards (Dieudonné, 2016; Köteles et al., 2011). Perceptions of environmental exposures, perceived health risks and worries play an important role in symptom experiences (Petrie et al., 2001; Porsius et al., 2015a; Rief et al., 2012). The type of symptoms that people report and associate with an environmental hazard differs depending on biological characteristics of the hazard and the content of media reports (Spurgeon, 2002; Witthöft and Rubin, 2013). There are differences in the degree to which environmental exposures can be sensorially detected by humans, and this may affect perceived exposure. For RF-EMF from mobile phone base stations, only the exposure source can be perceived (f.i. visibility of antennas on nearby buildings). While black smoke or diesel exhaust can sometimes be seen on windows, or smelt, there is no sensory system in humans that can directly perceive the level of air pollutants such as NO_2. Traffic noise is the only exposure, in this study, which is perceived by a specific sensory system in humans (Muzet, 2007) and we therefore expect higher correlations with self-reported perceived exposure than for air pollutants and in particular RF-EMF.

1.1. Aims and research questions

This paper applies insights from epidemiological and psychosocial research to study environmental determinants of symptom-based health outcomes within the Dutch population-based Occupational and Environmental Health Cohort study (AMIGO). We have formulated three research questions, with the purpose of achieving a better understanding of the interplay between environmental exposures, perceptions and reported symptoms: 1) To what extent are participants able to assess personal exposure levels, and how does this differ between environmental exposures?; 2) What are the associations between modeled exposures and symptom-based health outcomes, and between perceived exposures and symptom-based health outcomes, and how do these associations change when both modeled and perceived exposures are taken into account simultaneously?; 3) Lastly, what is the impact on perceived exposures and on symptom-based health outcomes, after a change in exposures due to moving to a different home? With these final longitudinal analyses, we aim to improve our understanding of the processes that underlie the relations between modeled and perceived exposures, and symptom-based health outcomes.

2. Material and methods

2.1. Study population

Data for this study were collected within the Dutch population-based AMIGO cohort. This cohort was set up in 2011 and 2012 to study environmental and occupational determinants of chronic diseases and symptoms in the general population (see (Slottje et al., 2014) for a full description of the AMIGO cohort). Participants were recruited through general practices, and were 31–65 years old at baseline (T0, 2011/2012). Of the invited 93,849 people, 14,829 participants responded (participation rate = 16%). A follow-up questionnaire was conducted in 2015 (T1, invited n = 14,597, response = 7905; 54%), to assess changes in exposure perceptions and symptom-based health outcomes.

2.2. Symptom based-health outcomes

Self-reported symptom-based health outcomes (non-specific symptoms, sleep disturbances and respiratory symptoms) were assessed with the baseline and follow-up questionnaires. Non-specific symptoms were assessed with the somatization scale of the Four-Dimensional Symptom Questionnaire (4DSQ-S) (Terluin et al., 2006), which consists of 16 non-specific somatic symptoms commonly reported in general practices (e.g. headaches, low back pain, and dizziness). Participants indicated for each symptom whether they were bothered by it during the previous week on a 5-point scale. The scores per symptom were trichotomized (no = 0; sometimes = 1; regularly/often/constantly = 2) and then summed over the symptoms to obtain a total score. Sleep disturbances were measured with the items of the Medical Outcomes Study (MOS) (Hays et al., 2005). The sleep problem index 9 was calculated following the instructions described in Hays et al. (2005) as a measure of overall sleep quality. Higher scores indicate more sleep disturbance, or lower sleep quality. Respiratory symptoms were assessed with items from the European Community Respiratory Health Survey II (Burney et al., 1994). A measure for respiratory symptoms is calculated as the sum of five items based on the method used by Sunyer et al. (2007). A higher respiratory score indicates more respiratory symptoms.

2.3. Modeled environmental exposures

The home addresses were geocoded using data from the Netherlands Cadastre, Land Registry and Mapping Agency (Kadaster Netherlands). The geocoded home addresses were linked to various spatial models to assess exposure at the home addresses of participants as a proxy for actual exposure. Exposures were modeled for both baseline (2011/2012) and follow-up (2015) home addresses. For noise and air pollutants, the model estimates only changed if participants moved to a different home, as other input variables in the exposure models were not updated over time.

RF-EMF exposure from mobile phone base stations was modeled with the 3D-geospatial model NISMap. The applicability of this model for epidemiological studies has been described in a number of previous studies (Beekhuizen et al., 2014; Bürgi et al., 2008). The model uses detailed information about 3D building data, topography, bedroom elevation, antenna location, antenna characteristics and radiation patterns to compute the field strength of GSM900 (Global System for Mobile Communication), GSM1800, and UMTS (Universal Mobile Telecommunications System) frequencies at the geocoded addresses in mW/m^2. Information about location and characteristics of antennas was available for 2011, 2012, and 2013. Input data closest to the questionnaire completion date was used for baseline and follow-up estimates.

Road traffic noise exposure was estimated by the Standard Model Instrumentation for Noise Assessments (STAMINA), which is a model to map environmental noise from various sources in the Netherlands (Baliatsas et al., 2016; Scheurs et al., 2010). Input variables for the calculations were information on noise sources (for road traffic noise this includes traffic intensities, speed, composition and type of road surface), building data, and ground type. We used noise levels (dB) estimated over a whole day period (Lden), which uses penalties for the evening and night. In practice there is a very high correlation between whole day period noise estimates and night time noise estimates as shown in an earlier Dutch study (r_{Sp} of 0.99) (Baliatsas et al., 2016). Uncertainty in the modelling of noise at low levels and lack of information on roads with low volumes of traffic led to the introduction of a cut-off value of 24 dB Lden for the noise level.

Long-term residential ambient air pollutant concentrations of NO_2 (nitrogen dioxide), NO_X (total concentration of NO and NO_2), $PM_{2.5}$ and PM_{10} (particles with an aerodynamic diameter ≤ 2.5 μm and ≤ 10 μm, respectively) were assessed using land-use regression (LUR) models developed within the European Study of Cohorts for Air Pollution Effects (ESCAPE) (Beelen et al., 2013; Eeftens et al., 2012), following a standardized protocol described elsewhere (Beelen et al., 2013; Eeftens et al., 2012). Air pollution measurements used to develop the LUR models took place between 2008 and 2011. NO_2 was the primary air pollutant metric, as this exposure is primarily traffic related, corresponding with our perceived exposure measure. Results for other air pollutants: NO_X, $PM_{2.5,}$ PM_{10} are reported in the Appendix.

2.4. Perceived environmental exposure

Perceived exposure was assessed at both time points (T0, 2011/2012 and T1, 2015) for the environmental exposures with the question: "To what extent are you exposed to: (1) electromagnetic fields/radiation from base stations for mobile phones, radio or television; (2) noise from road traffic in your home neighborhood; (3) air pollution in the residential area from road traffic?" Answers were given on a 7-point Likert scale ranging from 0 = not at all, to 6 = very much.

2.5. Covariates

The baseline questionnaire included questions on sex, age (in years), highest attained level of education (classification according to Statistics Netherlands), and smoking (never, ever, current). Low neighborhood income (percentage of income earners in the neighborhood with an income lower than the 40th percentile of the national income distribution) as an indication of neighborhood socioeconomic position was obtained from Statistics Netherlands (2012).

2.6. Statistical analysis

We reported the baseline characteristics of the study participants and summary statistics for modeled and perceived environmental exposures (RF-EMF, noise, air pollutants), as well as the various health outcomes (non-specific symptoms, sleep disturbances, respiratory symptoms), for the two time points used in this study (T0, 2011/2012 and T1, 2015). We calculated Spearman correlations between all variables of interest at baseline (e.g. the correlation among all three modeled exposures, among all three perceived exposures, among the different symptom-based health outcomes, and the correlation between modeled and corresponding perceived exposure). The correlation between modeled exposure and the corresponding perceived exposure is interpreted as an indication of the accuracy in which participants were able to assess personal exposure levels.

Associations between modeled exposures, perceived exposures and the symptom-based health outcomes (second research question) were analyzed with mixed models. We performed both single predictor models (including modeled or perceived exposure, respectively) and two-predictor models (including modeled and perceived exposure simultaneously). We then used fixed effect models (Bell et al., 2015) in the follow-up sample to analyze temporal changes, i.e. whether intra-individual variation in perceived exposure was associated with intra-individual variation in health outcomes. Modeled exposure was not included in these analyses, as there was no temporal variation in estimates for air pollutants and noise unless participants moved to a different home address.

To assess the impact of a change in the environment on modeled, perceived exposures and symptom-based health outcomes (last research question), we analyzed only the group of participants who had moved between baseline and follow-up and participated in both questionnaires (n = 592). Only for this group there were participants with sufficient temporal variation in modeled exposure estimates to evaluate the impact thereof on health outcomes. We first plotted the course of perceived exposure (means) over time for three percentile-based categories of absolute change (T1-T0) in modeled exposure (decrease: 0–20, no or small change: 20–80, increase: 80–100). Finally, we performed fixed effect models for the group of movers, including both modeled and perceived exposures as predictors.

Perceived and modeled exposures were analyzed as continuous variables with the exception of RF-EMF from mobile phone base stations. Because a large percentage of participants had modeled RF-EMF levels at or near 0.000 mW/m^2, values were dichotomized based on the 90th percentile of baseline exposure, with values ≤ 0.050 mW/m^2 defined as low and >0.050 mW/m^2 defined as high, similar to Martens et al. (2017). The health outcomes are analyzed continuous. All mixed models were adjusted for sex, age, education, smoking, neighborhood income level, and for year of filling in the questionnaire (baseline/follow-up). The fixed effect model controls for all measured and unmeasured stable characteristics of an individual (Bell et al., 2015) and therefore no covariates were included in the model.

Missing values ranged between 0% and 7%. Missing values were imputed using the fully conditional method (FCS) in SAS. This method applied a discriminant function for categorical variables and predictive mean matching for continuous variables. A p-value of 0.05 was used as the cut-off for statistical significance. The statistical analyses were carried out using SAS (SAS Institute Inc., Cary, NC, USA).

3. Results

3.1. Descriptive statistics

Baseline characteristics of the AMIGO participants at baseline (n = 14,829) and follow-up (n = 7905) are shown in Table 1. Participants who filled in the follow-up questionnaire (follow-up sample) were more often higher educated, less often current smokers, on average older (Table 1), and had more favorable symptom scores at baseline (Table 2) than the baseline cohort. The follow-up sample had similar scores at baseline for modeled exposures and perceived exposures, compared to participants who participated only at baseline (Table 2). Over time, perceived exposures increased, and sleep disturbance and respiratory symptoms decreased in the follow-up sample. Modeled exposure values ranged from 0.00–3.13 mW/m^2 for RF-EMF, 27.00–74.80 dB for noise, and 10.25–68.39 μg/m^3 for NO_2 at baseline.

3.2. Correlations

Table 3 shows the Spearman correlations between modeled exposures (RF-EMF, noise, air pollutants), perceived exposures, and symptom-based health outcomes (non-specific symptoms, sleep disturbances and respiratory symptoms). Correlation clusters were identified among the three modeled exposures (r_{Sp} 0.18–0.41), between modeled and corresponding perceived exposures (r_{Sp} RF-EMF = 0.11, noise = 0.40, NO_2 = 0.34), among the three perceived exposures (r_{Sp} 0.42–0.76), and the three health outcomes (r_{Sp} 0.27–0.50).

3.3. Effects of modeled and perceived exposure on symptom-based health outcomes

Table 4 summarizes the results of mixed model analyses of all perceived and modeled exposures and the different health outcomes. Modeled RF-EMF exposure was not significantly associated with respiratory symptoms and sleep disturbances, but was associated with lower non-specific symptom score in the single-predictor model. Perceived RF-EMF exposure was significantly associated with worse health outcomes in all single- and two-predictor analyses.

Modeled noise exposure was significantly associated with worse scores on health outcomes in the single-predictor models. Modeled noise exposure was associated with less sleep disturbance in the two-predictor model. Perceived noise exposure was significantly associated with worse health outcomes in all single- and two-predictor analyses.

Modeled NO_2 was significantly associated with worse scores on each health outcome in the single predictor models and in the two-predictor models, although effects of NO_2 diminished when perceived exposure was included in the two-predictor model. Perceived exposure to air pollution from road traffic was significantly associated with worse health outcomes in all single- and two-predictor analyses. Results for NO_x, $PM_{2.5}$, and PM_{10} were similar (Appendix Table A.1.), although the majority of the associations for these modeled air pollutants were not significant in the two-predictor models.

Table 5 summarizes the results of the fixed effect analyses in which temporal changes on an individual basis (between T0 and T1) in perceived exposure were related to changes in symptom reporting for the follow-up sample (n = 7905). For all environmental exposures, changes in perceived exposure were significantly associated with corresponding change in non-specific symptoms. Change in perceived RF-EMF exposure from base stations and noise exposure was significantly associated with a corresponding change in sleep disturbance. Change in perceived air pollution from road traffic was significantly associated with a corresponding change in respiratory symptoms.

3.4. Effects of a change of environment

In total 1224 (8.25%) participants moved to a different home between baseline in 2011/2012 (T0) and the follow-up questionnaire in

Table 1
General baseline (2011/2012) characteristics for the baseline cohort (n = 14,829) and follow-up sample (n = 7905) in AMIGO.

Variable	Baseline cohort (n = 14,829)		Follow-up sample (n = 7905)	
	n	%	n	%
Sex				
Male	6561	44.24	3728	47.16
Female	8268	55.76	4177	52.84
Education				
Low	4714	31.79	2246	28.41
Medium	4773	32.19	2420	30.61
High	5342	36.02	3239	40.97
Smoking status				
Never	6748	45.51	3685	46.62
Ever	5755	38.81	3239	40.97
Current smoker	2326	15.69	981	12.41
	Mean (SD)	IQR	Mean (SD)	IQR
Age (years)	50.65 (9.37)	43.00–59.00	52.17 (9.04)	46.00–60.00
Socioeconomic position (%)[a]	39.41 (6.92)	35.00–44.00	39.16 (6.87)	34.00–44.00

[a] Percentage income-earners with a low-income in the neighborhood.

Table 2
Exposure and health outcome characteristics for the baseline AMIGO cohort (n = 14,829) at T0 (2011/2012) and the follow-up sample (n = 7905) at T0 (2011/2012) and T1 (2015).

Variable	Baseline cohort T0 (n = 14,829)		Follow-up sample T0 (n = 7905)		Follow-up sample T1 (n = 7905)	
	Mean (SD)	IQR	Mean (SD)	IQR	Mean (SD)	IQR
Modeled RF-EMF (mW/m^2)	0.02 (0.09)	0.00–0.01	0.02 (0.09)	0.00–0.01	0.03 (0.11)	0.00–0.02
Modeled noise (dB)	53.11 (5.82)	49.40–56.70	53.15 (5.86)	49.40–56.70	53.14 (5.86)	49.40–56.70
Modeled NO_2 (μg/m^3)	22.11 (5.60)	18.30–25.53	22.22 (5.59)	18.44–25.64	22.19 (5.60)	18.38–25.61
Perceived base station (0–6)	1.05 (1.26)	0.00–2.00	1.02 (1.21)	0.00–2.00	1.22 (1.45)	0.00–2.00
Perceived noise (0–6)	1.65 (1.48)	1.00–2.00	1.62 (1.44)	1.00–2.00	1.96 (1.58)	1.00–3.00
Perceived air pollution (0–6)	1.83 (1.55)	1.00–3.00	1.82 (1.52)	1.00–3.00	2.17 (1.64)	1.00–3.00
Non-specific symptoms (0–32)	5.96 (5.24)	2.00–8.00	5.66 (5.00)	2.00–8.00	5.64 (4.93)	2.00–8.00
Sleep disturbances (0–100)	27.18 (14.71)	16.11–35.56	26.42 (14.28)	15.56–33.89	25.40 (14.26)	15.56–33.33
Respiratory symptoms (0–5)	0.48 (0.97)	0.00–1.00	0.44 (0.91)	0.00–1.00	0.40 (0.87)	0.00–0.00

SD = standard deviation, IQR = interquartile range, RF-EMF = radiofrequency electromagnetic fields, NO_2 = nitrogen dioxide.

2015 (T1); of these, 592 participants filled in both questionnaires. This change of environment resulted in changed modeled and perceived exposures. Moved participants were categorized into three percentile based categories of change in absolute modeled exposure (decrease: 0–20 percentile, no change: 20–80, increase: 80–100). The cut-off points of the categories for the absolute change in modeled exposure are presented in Appendix Table A.2. Fig. 1 presents the course of mean perceived exposures over time for participant groups with a decrease, no or small change, and increase in modeled exposure after moving. For participants with an increase in modeled exposure, the corresponding average perceived exposure increased as well in the same time period, in particular for NO_2 and noise. For participants with a decrease in modeled exposure, the corresponding average perceived exposure decreased as well over time for noise and NO_2, but not for RF-EMF. Appendix Table A.3. shows that intra-individual variation in perceived exposures and modeled exposures were not significantly associated with any intra-individual variation in symptom-based health outcomes, except for perceived RF-EMF, which was significantly associated with intra-individual variation in non-specific symptoms and sleep disturbance.

4. Discussion

In this prospective cohort study, we examined the interplay between three modeled and perceived environmental exposures (RF-EMF from mobile phone base stations, noise and air pollutants from road traffic) and three symptom-based health outcomes (non-specific symptoms, sleep disturbances, and respiratory symptoms).

4.1. Correlation clusters

It seems that beliefs of participants about their exposure level to noise and air pollutants corresponded to some extent with their modeled exposure level, whereas this was not apparent for RF-EMF. In line with previous work (Martens et al., 2017), we found low correlations between modeled and perceived exposure to RF-EMF from mobile phone base stations. The low levels of knowledge regarding RF-EMF in the general population (Claassen et al., 2015) likely plays a role. For example, the extent to which the exposure can be detected by the senses, and the visibility of nearby exposure sources. As expected, we found higher correlations between modeled and perceived exposure for

Table 3
Spearman correlation coefficients for modeled exposures, perceived exposure and symptom-based health outcomes in the AMIGO baseline cohort (n = 14,829, T0 = 2011/2012).

		Modeled exposure			Perceived exposure			Symptom-based health outcomes		
		RF-EMF (mW/m^2)	Noise (dB)	NO_2 (μg/m^3)	Base station	Noise	Air pollution	Non-specific symptoms	Sleep disturbances	Respiratory symptoms
Modeled exposure	RF-EMF (mW/m^2)									
	Noise (dB)	0.18								
	NO_2 (μg/m^3)	0.39	0.41							
Perceived exposure	Base station	0.11	0.11	0.15						
	Noise	0.14	0.40	0.28	0.42					
	Air pollution	0.15	0.35	0.34	0.46	0.76				
Symptom-based health outcomes	Non-specific symptoms	0.03	0.03	0.05	0.10	0.12	0.10			
	Sleep disturbances	0.03	0.03	0.06	0.13	0.14	0.12	0.50		
	Respiratory symptoms	0.03	0.03	0.05	0.06	0.07	0.08	0.37	0.27	

All correlations are significant with p-values < 0.005.
RF-EMF = radiofrequency electromagnetic fields, NO_2 = nitrogen dioxide.
Darker colors indicate higher correlations.

Table 4
Mixed model analyses of Modeled and Perceived Exposure to RF-EMF from Mobile Phone Base Stations, Traffic Noise and Road Traffic Air Pollution on Non-specific symptoms, **Sleep disturbances**, and **Respiratory symptoms** for AMIGO respondents (n = 14,829, T0 = 2011/2012 and n = 7905, T1 = 2015).

		Non-specific symptoms (0–32)		Sleep disturbances (0–100)		Respiratory symptoms (0–5)	
		β (95%CI)[a]	p	β (95%CI)[a]	p	β (95%CI)[a]	p
RF-EMF							
1	Modeled (0–1)	−0.23 (−0.43,-0.03)	0.026[b]	−0.58 (−1.15,0.00)	0.051	−0.03 (−0.07,0.01)	0.096
2	Perceived (0–6)	**0.37 (0.32,0.40)**	**0.000**	**0.81 (0.68,0.94)**	**0.000**	**0.04 (0.03,0.05)**	**0.000**
3	Modeled (0–1)	−0.13 (−0.33,0.07)	0.201	−0.36 (−0.94,0.22)	0.222	−0.02 (−0.06,0.02)	0.305
	Perceived (0–6)	**0.37 (0.32,0.41)**	**0.000**	**0.80(0.67,0.93)**	**0.000**	**0.04 (0.03,0.05)**	**0.000**
Noise							
1	Modeled (dB)	**0.02 (0.01,0.03)**	**0.001**	**0.05 (0.01,0.09)**	**0.008**	**0.00 (0.00,0.01)**	**0.002**
2	Perceived (0–6)	**0.30 (0.26,0.35)**	**0.000**	**0.83 (0.72,0.95)**	**0.000**	**0.04 (0.03,0.05)**	**0.000**
3	Modeled (dB)	−0.01 (−0.03,0.00)	0.067	−0.04 (−0.08,−0.00)	0.028[b]	-0.00 (−0.00,0.00)	0.655
	Perceived (0–6)	**0.32 (0.28,0.36)**	**0.000**	**0.88 (0.76,1.01)**	**0.000**	**0.04 (0.03,0.05)**	**0.000**
NO_2							
1	Modeled (μg/m^3)	**0.05 (0.04,0.06)**	**0.000**	**0.15 (0.11,0.19)**	**0.000**	**0.01 (0.01,0.01)**	**0.000**
2	Perceived (0–6)	**0.27 (0.23,0.31)**	**0.000**	**0.67 (0.56,0.78)**	**0.000**	**0.04 (0.03,0.05)**	**0.000**
3	Modeled (μg/m^3)	**0.02 (0.01,0.04)**	**0.001**	**0.10 (0.05,0.14)**	**0.000**	**0.00 (0.00,0.01)**	**0.000**
	Perceived (0–6)	**0.25 (0.21,0.29)**	**0.000**	**0.59 (0.48,0.71)**	**0.000**	**0.04 (0.03,0.06)**	**0.000**

1. These are the single predictor models for modeled exposure. 2. These are the single predictor models for perceived exposure. 3. These are the two-predictor models, i.e. including both modeled and perceived exposure.
Adverse effects are printed in bold if the p-value is lower than 0.05. RF-EMF = radiofrequency electromagnetic fields, PM = particulate matter, NO_2 = nitrogen dioxide.
[a] Adjusted for baseline values of sex, age, education, smoking, socioeconomic position, and year (baseline/follow-up).
[b] Beneficial effects with p-value below 0.05.

noise exposure from traffic (Davies et al., 2009). For air pollution from road traffic, correlations between modeled and perceived exposure were only slightly lower than for noise exposure. Perhaps familiarity with the link between road traffic and exposures, the visibility, noise, or smell of exhaust of nearby roads gave participant an indication of exposure near the home. We found moderate correlation clusters among the three modeled exposures, and substantial correlation clusters among the three perceived exposures and three different symptom-based health outcomes. As expected, we found correlations among modeled exposures, likely due to the clustering of exposures in urbanized areas. Correlation clusters among perceived exposures could be explained by a general environmental health worry factor (Petrie et al., 2005), as well as the clustering of actual exposures. Correlations among health outcomes may be partly explained by underlying factor, representing a general tendency to report symptoms (Porsius et al., 2015b). The presence of substantial correlation clusters among modeled exposures, perceived exposures, and health outcomes, implicates that disentanglement of different exposures and their individual health effects may prove difficult in epidemiological research.

4.2. Effects of modeled and perceived exposure on symptom-based health outcomes

Modeled RF-EMF was not associated with higher symptom scores, which is in line with earlier conducted studies (Baliatsas et al., 2015; Frei et al., 2012; Martens et al., 2017). For modeled noise exposure, prior studies on self-reported health (Muzet, 2007; Öhrström, 1989; Pirrera et al., 2010) indicated that noise is mainly associated with increased sleep disturbances, and air pollutants mainly with respiratory symptoms (Mar et al., 2004; Modig and Forsberg, 2007; Patel et al., 2010). The results of single predictor models in this study confirm the presence of significant adverse effects of noise and air pollutants on symptom scores. Contrary to our expectations, these health effects extended across all assessed health outcomes, even those not previously reported in literature. However, the results were notably different in the two-predictor models, that included both modeled and perceived exposures. Significant adverse effects of modeled exposures on health outcomes generally disappeared (noise) or severely diminished (NO_2), when perceived exposure was included in the model. In two analyses (Table 4: effect of RF-EMF on non-specific symptoms, effect of noise on sleep disturbance) we found unexpected beneficial effects of modeled exposures, but these effects were small and possibly coincidental findings. The results do not necessarily imply the absence of causal effects of actual exposure on symptom scores, but do highlight the importance of exposure perceptions and a need to clarify the underlying causal mechanisms. The associations with symptom scores indicate a greater maximum impact of perceived than modeled exposure on symptom scores, for both single- and two-predictor models (as is shown in Appendix Table A.4.). These findings indicate that perceptions of exposures can play an important role when studying environmental determinants of symptom-based health outcomes.

A sizable minority of the participants reported high scores on perceived exposure levels. High scores on perceived exposures are likely

Table 5
Fixed effect analyses for effects of intra-individual changes in Perceived Exposure to Mobile Phone Base Stations, Noise and Air Pollution on intra-individual changes in **Non-specific symptoms**, **Sleep disturbances**, and **Respiratory symptoms** for AMIGO respondents (n = 7905) who participated at T0 (2011/2012) and T1 (2015).

	Non-specific symptoms (0–32)		Sleep disturbances (0–100)		Respiratory symptoms (0–5)	
	B (95%CI)	p	B (95%CI)	p	B (95%CI)	p
Perceived base station (0–6)	**0.16 (0.10, 0.22)**	**0.000**	**0.19 (0.01, 0.36)**	**0.042**	0.01 (−0.00,0.02)	0.161
Perceived noise (0–6)	**0.07 (0.01, 0.13)**	**0.021**	**0.21 (0.03, 0.39)**	**0.019**	0.01 (−0.01,0.02)	0.311
Perceived air pollution (0–6)	0.04 (0.02, 0.10)	0.184	0.08 (−0.09, 0.25)	0.344	**0.01 (0.00,0.03)**	**0.049**

Adverse effects are printed in bold if the p-value is lower than 0.05.

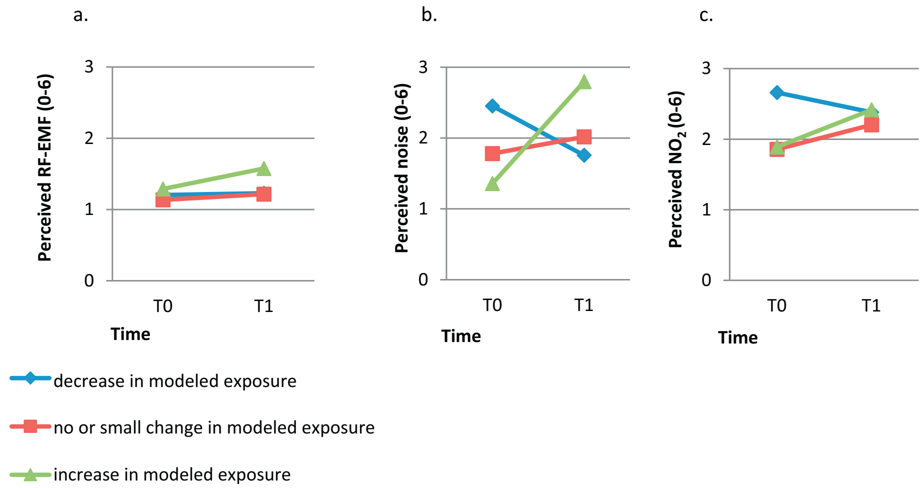

Fig. 1. (Color). Course of mean perceived exposures (a = RF-EMF, b = Noise, c = NO_2) over time (T0 = 2011/2012, T1 = 2015) for AMIGO respondents who moved house between T0 and T1 (n = 592) for percentile based categories (0–20, 20–80, 80–100) of absolute change in the corresponding modeled exposure.

to be in part the result of features of the environment that also drive modeled exposure levels (such as the proximity of nearby roads). In addition, worries about potential health effects of the specific exposure, and worries about environmental risks in general (Petrie et al., 2001), can influence perceived exposure scores. A part of the cohort participants moved to a new home (n = 592), and therefore changed their residential environment which often affected their modeled exposure levels. For this group, we found that a substantial increase or decrease in modeled exposure with respect to noise and air pollution (NO_2) was coupled with a simultaneous increase, respectively decrease in the corresponding perceived exposure (Fig. 1). This longitudinal evidence strengthens the conclusion that participants are to some extent aware of, and able to estimate, the level of these two environmental exposures in their residential environment. The observed relation with change in perception was less distinct for RF-EMF from mobile phone base stations. Here, risk perception and health concerns appear to influence perceived exposure to a greater extent than exposure cues such as visibility of nearby base stations. In the group of follow-up participants (n = 7905), change in perceived exposures was significantly positively associated with change in most symptom-based health outcomes in the fixed effect analyses. This finding was not replicated in the smaller group of moved participants (n = 592), except for positive effects of change in perceived RF-EMF on change in non-specific symptoms and sleep disturbance. However, due to the small number of movers, the power to detect such associations was limited in this subgroup. A change in perceived exposure in a new residential environment can be important given the associations between higher exposure perception and increased symptom scores, which were in line with earlier studies (Claeson et al., 2013; Frei et al., 2014; Fyhri and Klæboe, 2009; Héritier et al., 2014).

The implications of these findings in combination with the role of modeled exposures depend on the underlying causal mechanisms. A causal link from the exposure source both to modeled exposure (as a proxy of the true exposure level) and to perceived exposure is plausible (Lima, 2004), based on observability of exposure sources, and supported by the results of this study. For exposures that can be sensorially observed (f.i. noise) sensitivity and annoyance can play role as mediator (Héritier et al., 2014) in the association between perceived exposure and symptom scores. In addition, there is sufficient evidence for the existence of nocebo effects (Porsius et al., 2016; Szemerszky et al., 2010; Witthöft and Rubin, 2013), to support a causal link between perceived exposure and reported symptoms through negative health expectations when participants think they are exposed. If such nocebo effects occur in this population, mediation effects of exposure on symptom scores through perceived exposure would be likely. Such mediation mechanisms can have an impact on epidemiological studies examining environmental determinants of symptom-based health outcomes. When perceived exposure is not taken into account, indirect health effects through perceived exposure may be incorrectly ascribed to modeled exposures. However, the importance of such mediation mechanisms could be overestimated. Nocebo mechanisms have been mainly studied in laboratory and field-experiment studies, but the extent to which they are important for associations between perceived exposures and reported symptoms in the general population is unknown. Mechanisms of reversed causation may also play a role. For example, participants with health problems with an unknown cause may become more aware of exposures in their environment, and incorrectly start attributing these to environmental sources (de Graaff, 2016; Dieudonné, 2016; Köteles and Simor, 2013). They experience and report their perceived exposure levels differently than healthy participants, which often is described as recall bias in epidemiological research and can be a problem in cross-sectional research and case-control studies. In this longitudinal study, with the use of a qualitative measure of perceived exposure, that is intended to capture the subjective experience of self-reported exposure, it perhaps is better described as a process of reversed causation. Depending on characteristics of the individual, but also features of the environment and changes in exposure, different processes underlying causal mechanisms of the link between exposure perceptions and symptom experiences could be important. Clarifying the underlying mechanisms is of great interest and importance for both epidemiological and psychosocial research disciplines, because of the implications for the interpretation of the relationships between the environment, perception, and symptom experiences. In addition, the need for effective public health intervention measures and policy implications varies depending on the importance of different mechanisms. Intervention measures targeted at reducing negative health expectations will only be effective in reducing symptom scores if the nocebo mechanism is the main explanation for the associations between exposure perception and reported symptoms.

4.3. Strengths and limitations

The study had a large study population for studying the symptom-based health outcomes of interest. In addition, there were observations at two points in time, allowing for longitudinal analyses for a subset of participants. Thirdly, all studied environmental exposures were modeled using validated geospatial models that have been used in previous epidemiological research (Baliatsas et al., 2016; Beelen et al., 2013; Eeftens et al., 2012; Martens et al., 2016). These models do not require extensive manual data-collection, allowing for research in large country-wide cohort studies. A limitation of the current study was that we only had modeled estimates for noise and air pollutants for one point in time (i.e. baseline), because input data for the geospatial models was not available for different years. Although estimates for noise and air pollutants would have improved slightly with new input data, large changes in exposure are not expected in this relatively short time frame. Eeftens et al. (2011) showed that NO_2 decreased only slightly between 1997 and 2007 and correlations were high (Eeftens et al., 2011). Another limitation concerns RF-EMF, where we modeled exposure from mobile phone base stations while the question about perceived exposure also included radio and tv base stations, because we expected people to not be familiar with differences between mobile phone and radio/tv base stations. However, given that mobile phone base stations are by far more present in residential areas than base stations for radio and tv, we expect these to dominate perceived base station levels.

4.4. Conclusion

Our study covered three environmental exposures, both modeled and perceived, and three symptom-based health outcomes. Correlations between modeled and perceived exposures appeared to be influenced by the observability of the exposure sources. Perceived exposures were consistently associated with increased symptom scores. In general, modeled exposures (except RF-EMF) were associated with increased symptom scores, but these associations disappeared or strongly diminished when perceived exposure was also added as a predictor. Under the reasonable assumption that perceived exposure is not a better proxy of the actual exposure than modeled exposure, these results would indicate that perceived exposure captures an additional element of the exposure that is not captured by the modeled exposure. When environmental determinants of symptoms are studied without acknowledging the potential role of these exposure perceptions, there is a risk of bias in the health effects attributed to modeled exposures. However, the etiological role of exposure perceptions in relation to symptom reporting requires further research. By combining insights from epidemiological and psychosocial research we have highlighted a range of complex issues that previously received little attention, but which can have important implications for interpretation of associations of interest, public health policy and intervention strategies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.05.007.

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