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Ecological momentary assessment study of exposure to radiofrequency electromagnetic fields and non-specific physical symptoms with self-declared electrosensitives

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ABSTRACT

The main objective of the study is to determine if non-specific physical symptoms (NSPS) in people with self-declared sensitivity to radiofrequency electromagnetic fields (RF EMF) can be explained (across subjects) by exposure to RF EMF. Furthermore, we pioneered whether analysis at the individual level or at the group level may lead to different conclusions. By our knowledge, this is the first longitudinal study exploring the data at the individual level.

A group of 57 participants was equipped with a measurement set for five consecutive days. The measurement set consisted of a body worn exposimeter measuring the radiofrequency electromagnetic field in twelve frequency bands used for communication, a GPS logger, and an electronic diary giving cues at random intervals within a two to three hour interval. At every cue, a questionnaire on the most important health complaint and nine NSPS had to be filled out.

We analysed the (time-lagged) associations between RF-EMF exposure in the included frequency bands and the total number of NSPS and self-rated severity of the most important health complaint. The manifestation of NSPS was studied during two different time lags - 0–1 h, and 1–4 h - after exposure and for different exposure metrics of RF EMF. The exposure was characterised by exposure metrics describing the central tendency and the intermittency of the signal, i.e. the time-weighted average exposure, the time above an exposure level or the rate of change metric.

At group level, there was no statistically significant and relevant (fixed effect) association between the measured personal exposure to RF EMF and NSPS.

At individual level, after correction for multiple testing and confounding, we found significant within-person associations between WiFi (the self-declared most important source) exposure metrics and the total NSPS score and severity of the most important complaint in one participant. However, it cannot be ruled out that this association is explained by residual confounding due to imperfect control for location or activities. Therefore, the outcomes have to be regarded very prudently. The significant associations were found for the short and the long time lag, but not always concurrently, so both provide complementary information. We also conclude that analyses at the individual level can lead to different findings when compared to an analysis at group level.

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1. Introduction

It is widely recognized that exposure to radiofrequency electromagnetic fields (RF EMF) above certain established exposure limits is likely to cause adverse health effects due to heating (ICNIRP, 1998). RF EMF are generated at different frequencies used in communication and broadcast transmitters for wireless and mobile telecommunication, and radio and TV. Exposure limits are exceeded only in relatively rare situations, for instance in certain occupational settings, and the exposures normally encountered in everyday life tend to be much lower, representing only a small fraction of the guideline limits. This said, there is continuing concern that adverse health effects, such as cancer (Baan et al., 2011; IARC, 2013) and various non-specific physical symptoms (NSPS) (Baliatsas et al., 2012a), may occur due to long-term exposure at the low levels encountered in the every-day environment.

Even though epidemiological studies on possible health effects from exposure to RF EMF have been conducted, no associations with RF-EMF and NSPS in experiments or surveys have been established (Augner et al., 2012; Baliatsas et al., 2012a; Röösli et al., 2010; Rubin et al., 2010; Rubin et al., 2011). This may partly be the case because exposure was either modelled, or based on spot measurements, or the human experiments were done in non-realistic environments, rather than actual measurements by exposimeters worn on the body in an everyday setting (Frei et al., 2010). Even in a double blind provocation study in which participants were visited at home or another location where they felt comfortable, no participant was able to correctly identify when they were being exposed better than chance (Van Moorselaar et al., 2017). In all studies, the exposures was expressed as a measure of central tendency of exposure such as the arithmetic or geometric mean, while other characteristics of the exposure such as the intermittency of the signal, or the sudden switches in intensity, may be equally important.

Most population studies looking for possible associations with NSPS and using exposimeters were performed in the German MobilEe project and all had a cross-sectional design (Thomas et al., 2008a, 2008b, 2010; Heinrich et al., 2010, 2011: Juhász et al., 2011). Use of a longitudinal approach, although time and budget consuming, may lead to a better insight in the associations between RF EMF exposure and NSPS. A longitudinal approach, following a person during his every day activities, may show if there are types of exposure that lead consistently to a response, whilst others may not, even within the same frequency band.

Finally, if sensitivity to electromagnetic fields, also referred to as electro(hyper)sensitivity or idiopathic environmental intolerance attributed to electromagnetic fields (IEI-EMF), exists, it is likely to occur only in a small part of the population. Therefore, to increase chances of detecting an actually existing association participants should be selected that are self-declared electrosensitives. The prevalence of IEI-EMF in the population is estimated to be 1.5–5% (Hillert et al., 2002; Levallois et al., 2002; Schreier et al., 2006). Later reports mention up to 10.6% (Van Dongen et al., 2014). However, in Taiwan it was reported to be 13.3% in 2007 (Tseng et al., 2011), but it decreased to 4.6% by 2017 (Huang et al., 2018).

The main objective of the study is to determine if non-specific physical symptoms (NSPS) in people with self-declared sensitivity to radiofrequency electromagnetic fields (RF EMF) can be explained (across subjects) by exposure to RF EMF, measured during five days. The manifestation of NSPS was studied during two different time lags - 0–1 h, and 1–4 h - after exposure and for different exposure metrics of RF EMF. Furthermore, we pioneered whether analysis at the individual level may lead to different outcomes than at group level.

2. Materials and methods

Bogers et al. (2013) elaborately describe the design of this ecological momentary assessment (EMA) study. The following gives a short overview of the applied design.

2.1. Study population

We recruited 63 self-declared electrosensitive volunteers all over the Netherlands. The first 20 were recruited from participants in the so-called Emphasis project (Baliatsas et al., 2015). The following 43 we recruited through advertisements in local newspapers, social media, e.g. Facebook and twitter, and the website of the National Institute for Public Health and the Environment (RIVM). In both groups, participants were selected based on self-reported sensitivity to EMF measured with a five-point scale ("I am sensitive to antennas and devices using wireless communication (e.g., for radio, television, mobile phones, wireless internet, etc.)" (for details see Bogers et al., 2013). Exclusion criteria were: working in an environment in which the exposimeter would have a high risk of getting damaged such as in heavy industry or near a device producing high magnetic fields such as induction ovens. Excluded were also those who were not willing to wear an exposimeter for five consecutive days and/or filling out the diary about eight times each day. Volunteers received a printout of their exposure over five days and a compensation of 50 Euro if the requirements were fulfilled. The survey started May 2013 and ended December 2014.

2.2. Measurement set

The measurement sets consisted of an exposimeter worn on the body in a camera bag at the right hip, parallel to the body axis, measuring the radiofrequency electromagnetic field in 12 frequency bands used for communication, a GPS logger worn at the left shoulder, and an electronic diary giving cues at irregular intervals within a two to three hour interval. At every cue, a questionnaire on non-specific symptoms had to be filled out. Further, a time sheet on when the exposimeter was not worn, for instance during sleeping, sporting or wet activities, had to be kept.

The exposimeter of type EME Spy 121 (Satimo, Courtaboeuf, France, http://www.satimo.fr) measures in 12 frequency bands used for communication: FM radio (88–108 MHz), TV3 (174–233 MHz), TETRA (380–400 MHz), TV4&5 (470–830 MHz), GSM uplink (880–915 MHz), GSM downlink (925–960 MHz), DCS uplink (1710–1785 MHz), DCS downlink (1805–1880 MHz), DECT (1880–1900 MHz), UMTS uplink (1920–1980 MHz), UMTS downlink (2110–2170 MHz), WiFi (2400–2500 MHz). TV3 and TV4&5 were originally the bands for analog TV broadcasts. However, in the Netherlands all broadcasts are Digital Video Broadcasting Terrestrial (DVB-T) in the TV4&5 frequency band. Also part of the radio broadcasts are Terrestrial Digital Audio Broadcasting (T-DAB) at 174–230 MHz in the TV3 band. TETRA is the protocol used for emergency services (police, fire brigade, and ambulances). GSM (also called GSM900), DCS (also called GSM1800) and UMTS are the frequency bands for mobile phone communications. Downlink stands for transmission from the base station to the cell phone, uplink for transmission from the cell phone to the base station. The DECT band is used by cordless landline phones and baby phones. WiFi is the protocol for wireless internet, but microwave ovens also operate in this frequency band. To reach at least five consecutive days of measurements, the sampling frequency was set at every 36th second. The maximum memory capacity is 12,544 samples, leading to a dataset of approximately 125 h. The upper detection limit is 0.265 W/m^2 (10 V/m), the lower is 0.0066 mW/m^2 (0.05 V/m). The 95% combined standard uncertainty budget determined in a Gigahertz Transverse ElectroMagnetic (GTEM) cell due to repeatability, linearity in response, flatness of response and elevation arrival angle is frequency dependent and ranges from 4.3 to 6.1 dB (Bolte et al., 2011). The exposimeter does not have a display, and is therefore a blinded meter. Reading out the meter requires special software and a translation and calibration file, it is therefore unlikely that any of the participants had access to its measurements during the survey.

To prevent the occurrence of biases and minimize the uncertainty in the measurements (Bolte, 2016), the laboratory of the Royal

Netherlands Air Force determined for each exposimeter a multiplicative calibration correction factor for all 12 frequency bands (Bolte et al., 2011). The calibration measurements were performed in an anechoic chamber by measuring the response of the exposimeter to a standard, vertically polarised input signal of 2.5 V/m, with a frequency at the mid of the specific frequency band.

The GPS logger of type Adapt AD-850 (Adapt, London, United Kingdom, http://www.adapt-mobile.com/), measured every second for a period of 20 h until the battery depleted. In this way, the battery would only deplete at night when participants were asleep at home. Participants were asked to reload the battery at night. The GPS data were used to interpret and check the quality of the exposimeter readings in case of unexpectedly high or low RF EMF measurements.

The electronic diary was programmed on LG P-500 Optimus One smartphones running on Android 2.3 operating in flight mode without a SIM card. Special software for the diaries was developed using Java (Android V.2.2 or higher). The diary program is based on software written for Palm-OS personal digital assistants, which has been developed and used by Houtveen et al. (2010).

2.3. Metrics

Since every communication source sends with a specific protocol and modulation of the carrier frequency, characterizing the main features of the signal requires more than one metric. For instance, wireless internet through WiFi does not use a signal at gradually increasing or decreasing field strength, but an intermittent signal using bursts. The same is the case for the Time Division Multiple Access (TDMA) protocol used by GSM on the 900 and 1800 MHz frequency bands. The main factors describing the signal are: a metric for central tendency, most commonly the mean or median; a metric for the variability of the signal in the long term e.g. the standard deviation; and short term variations e.g. the rate of change metric (RCM) or the number of samples the field strength is above a certain level (Verrier et al., 2005). RCM is the root mean square of the first-difference and describes the variability, the intermittence of short term changes (Yost, 1999). The RCM is hardly influenced by changes in the long term (Kaune et al., 2001), and is therefore suitable for relatively small periods of two to three hours.

As a metric for central tendency we chose the time weighted average (TWA) and for intermittence we chose the time above a limit if the exposure tends to manifest in peaks (timeabove), and the RCM if the changes are intermittent, but not per se in peaks on a short time scale. From earlier measurements in surveys in the Netherlands during the EMF-AEM project we chose the limits for the timeabove as three times the TWA as measured in the microenvironment it occurs most hours (Bolte et al., 2008; Bolte and Eikelboom, 2012). Because some participants indicated to be sensitive to base stations for mobile telecommunications rather than to specific frequency bands, and to reduce the number of exposure variables, the frequency bands for GSM (900 and 1800 MHz) and UMTS (2100 MHz) were summed into one GSM/UMTS band: one for downlink, from base station to cell phone, and one for uplink, from cell phone to base station. The signals, in power density, of all previously named bands were also stacked in time to one Total frequency band. In case of WiFi we used both RCM and timeabove, as changes in WiFi exposure either occur when environments with a low WiFi field strength are changed for environments with a high field strength or vice versa, or exposure above a certain threshold occurs if large amounts of data are used by a wireless device such as working on a laptop, playing on a wireless game console or watching movies on a tablet. This led to the next frequency band - metrics: FM - TWA and time above 0.015 mW/m^2; DECT – TWA and time above 0.2 mW/m^2; GSMUMTS downlink – TWA and RCM; GSMUMTS uplink – TWA and RCM; WiFi – RCM and time above 0.1 mW/m^2; Total – TWA, RCM, and time above 0.2 mW/m^2. The Tetra and TV bands were not included as exposure in these frequency bands hardly occurred. The metrics were all calculated for two time lags: over a period from 0 to 1 h before the diary cue and over the period from 1 to 4 h before the diary cue.

2.4. Electronic diary and questionnaires

The electronic diary included questions on non-specific physical symptoms, and had to be filled out at random cues generated every two to three hours and just after waking up and before going to bed. At times a cue could not be answered, for instance during driving, the electronic diary had to be set in postpone mode. If a cue was given and not responded to, it was repeated after three minutes twice and then expired. On average over five days 39 cues per participant were given.

The diary questionnaire consists of 32 items and in the morning and evening five additional questions were included. General health status was assessed by using the first question from the RAND-36 (Van der Zee and Sanderman, 2012). Nine symptoms are selected that are most often reported by electrohypersensitive people according to studies in Switzerland (Röösli et al., 2004). Symptoms comprised fatigue, headache, distressed/nervous/tense feeling, concentration problems, tinnitus, dizziness or light-headedness, painful joints or muscles, skin problems, problems with vision, hearing or smell. For all symptoms the momentary experience was assessed (‘at this moment, …’). Response options ranged from ‘not at all’ to ‘very much’ on a five-point Likert response format with only the extremes labelled. During the survey at each random cue, the participants were asked to indicate the severity of their on most important symptom on a 5-point scale (0–4), see Supplement A.

Respondents were also asked to indicate what their most important symptom was and to rate the severity on a five point Likert scale. They gave their own description of their symptoms which were then categorized according to the nine standard NSPS. No one named dizziness, painful joints or muscles, skin problems or sensory problems as his most important symptom.

Location parameters were assessed in the electronic diary by asking participants to indicate the type of environment and type of area they were in (see (Bolte and Eikelboom, 2012)) during the time between alarm cues. The environments included: at home inside, at home outside, at work or educational institution, elsewhere inside, elsewhere outside, and travelling (on foot, by bike, car or public transport); the three types of area included: in the city centre or a shopping area, in a residential or built-up area but not the centre, outside the built-up area (e.g., in a rural area or in nature).

2.5. Data cleaning

If a participant did not fill out the diary, did not wear the exposimeter, or did not fill out the time sheet on when the exposimeter was worn, all data of this person were removed. If errors occurred due to mechanical failures of the smart phone or the exposimeter, we asked the participant to wear the measurement set again for five days.

Time periods between cues were excluded from the analysis if: the exposimeter had not been worn for half of the time of a time period; the measurements were recognized to be erroneous, for instance if the exposimeter had been mechanically damaged; for a lag of 0–1 h the time between cues was less than half an hour, for instance if within half an hour after a cue the participant went to bed; for a lag time of 1–4 h the time between cues was less than one hour and a half; the participant reported the smart phone or the exposimeter to be damaged or functioning in a deviant way.

2.6. Data analysis

Firstly, the strength and significance of the associations between the thirteen exposure metrics for both time lags and the two outcome measures (namely the sum score of symptoms, normalized sum score (0–1) and box-cox transformed sum score and the severity score on the most important complaint) was analysed by means of generalized correlation, the square root of a generalized R^2, at group level, i.e. the correlations were calculated of all cues of all participants, taking the clustering of the data within persons into account (Nakagawa and Schielzeth, 2013).

Subsequently, for each outcome, a linear mixed effects model was applied, with as fixed effect the exposure metric and potential confounders, and a random intercept for participant. The potential confounders included were sex, age, education, season, and hour of day. As perceived exposure to FM radio, uplink, downlink, DECT and WiFi was not associated with the most important complaint or sum score of complaints, nor with the actual exposure metrics, it was not regarded as a confounder. Hour of day was included as it is associated with symptom occurrence and severity (e.g., for fatigue). This was done by using a sinusoidal 24 h-function to account for the diurnal pattern. For statistically significant associations the percentage of explained variance was assessed.

Next, the measurements within each individual were analysed. First, linear mixed models were used to examine, within each individual, the relation between the exposure metrics for the self-declared main source and the outcome sum score of nine NSPS. Both with a 0–1 h time lag and a 1–4 h time lag. The exposure metrics were modelled nonparametric with a penalized B-spline (Eilers and Marx, 1996). Autocorrelation in the residuals was accounted for by a continuous autoregressive correlation structure of order one. The correlation depends on the time difference between subsequent measurements. In total 244 associations were tested and corrected for multiple testing by Holm's adjustment method. The remaining models with adjusted p-value below 0.05, were analysed further.

The associations were adjusted for potential confounders: hour of the day was included in the model as a penalized cyclic spline, location parameters entered the model as dummy variables. The thus fitted models were visually inspected for remaining serial correlation by means of partial autocorrelation plots of the residues. If needed the dependence between residuals was modelled with a more complex ARIMA correlation until remaining partial correlation was absent.

From these final analyses p-values for the associations between exposure metric and outcome were collected and again corrected for multiple testing. Only models with adjusted p-values < 0.05 were kept.

The same series of analyses were done with the scores for the self-declared main health complaint as an outcome variable. The linear mixed model does not seem to be ideally suited for this outcome, but appeared the only feasible distribution for this type of analysis.

Finally the relation between both outcome measures and perceived exposure to FM radio, uplink, downlink, DECT and WiFi was examined along the same lines, but here the exposure was modelled as a categorical variable with (at most) 5 levels. For each outcome measure 305 potential associations were examined and adjusted accordingly for multiple testing.

For all analyses the freely available statistical software package R version 3.5.3 (www.r-project.org) and the R packages nlme (version 3.1–137) and mgcv (version 1.8–24) were used.

3. Results

3.1. Description of study population and data

From the 63 volunteers, six were excluded: three did not fill out the electronic diary for all days and for the other three the electronic diary was incorrectly functioning, leading to a loss of the time or date stamp or only three questions asked at each cue. On average 84% of the cues were answered. The number of responded cues per participant over five days ranged from 10 to 46 with a mean of 32.5 and a standard deviation of 6.9.

Table 1 shows the descriptive data and confounders of the 57 participants. Clearly, women were overrepresented with 79%. For convenience, most measurements (42) were performed during spring and summer. A priori, a third of the participants reported multiple health complaints as most important complaint, even though specifically asked to fill out one complaint. The mean(sd) of the sum scores on NSPS (0–36) was 11.14 (5.24), ranging from 2.55 to 26.33. The mean(sd) of the severity of the most important symptom score (0–4) was 2.12(0.89), ranging from 0.38 to 3.94.

Table 1
Descriptive data of 57 participants.

		N	%
Sex	Men	12	21.1
	Women	45	78.9
Age	16–24	2	3.6
	25–34	15	26.3
	35–44	10	17.5
	45–54	13	22.8
	55–64	13	22.8
	65 <	4	7.0
Highest education	Primary	1	1.8
	Secondary – lower (pre-professional)	8	14.0
	Secondary – medium (pre-professional)	12	21.1
	Secondary – higher (college, pre-university)	11	19.3
	Professional – medium	1	1.8
	Professional – higher (applied sciences)	8	14.0
	University	11	19.3
	Other	5	8.8
Season[a]	Autumn	14	24.6
	Winter	2	3.5
	Spring	19	33.3
	Summer	23	40.4
Most important complaint (0–4)	Concentration problems	2	3.5
	Fatigue	8	14.0
	Headache	8	14.0
	Nervousness	4	7.0
	Tinnitus	7	12.3
	> 1 symptom	19	33.3
	Other	9	15.8
Most important complaint score	Mean(sd): 2.12(0.89)	57	
Sum score of 9 NSPS (0-36)	Mean(sd): 11.14(5.24)	57	
Most important source[b]	DECT	1	1.8
	Downlink	5	8.8
	Downlink-ELF	2	3.5
	ELF	4	7.0
	ELF-WiFi	3	5.3
	Multiple	2	3.5
	Other	1	1.8
	Unknown	16	28.1
	Uplink	4	7.0
	Uplink-WiFi	14	24.6
	WiFi	5	8.8

[a] Three participants started the first day in spring and the last four in summer.
[b] ELF = extremely low frequency magnetic fields.

The (combination of) frequency bands the participants attributed their most important complaint to were: DECT (1), downlink (5), downlink-ELF (2), ELF (4), ELF-WiFi (3), multiple (2), other (1), unknown (16), uplink (4), uplink-WiFi (14), WiFi (5). Thus, for only 36 participants their most important complaint could be attributed to at least one frequency band that could be measured by the exposimeters. Remarkably, 16 Participants did not know what was their main source of exposure leading to their health complaints, but were nevertheless convinced it must be RF-EMF. A group of 14 claimed both exposure to WiFi and uplink to be the cause of their most important health complaint. Four participants attributed it to working with computers not knowing whether it is due to exposure to the wireless internet or to sources of extremely low frequency (ELF) magnetic fields. Even though we specifically asked for sources of RF EMF, four participants actually attributed their most important complaint to an electric device

Table 2
Metrics over individual arithmetic means (N = 57) over five days of TWA in mW/m^2 and RCM short time lag (*1000) cues. Mean = arithmetic mean, geomean = geometric mean, sd = standard deviation, gsd = geometric standard deviation.

Source/metric	TWA total	TWA uplink	TWA downlink	TWA FM	TWA DECT	RCM WiFi	RCM total	RCM uplink	RCM downlink
Mean	0.399	0.139	0.05	0.033	0.083	0.284	1.285	0.753	0.041
sd	0.537	0.374	0.106	0.094	0.193	0.604	1.754	1.447	0.146
geomean	0.265	0.059	0.032	0.013	0.025	0.084	0.598	0.167	0.012
gsd	2.182	2.774	2.014	2.663	3.692	NA	2.930	NA	NA
0%	0.096	0.02	0.019	0.007	0.007	0.001	0.021	0.001	0
25%	0.158	0.024	0.021	0.007	0.009	0.03	0.286	0.053	0.007
50%	0.219	0.049	0.024	0.009	0.016	0.094	0.621	0.253	0.013
75%	0.363	0.088	0.033	0.019	0.034	0.176	1.254	0.721	0.027
100%	2.818	2.631	0.785	0.661	1.107	3.854	8.95	8.785	1.105

generating only ELF magnetic fields such as household appliances. Though earlier research indicate that exposure to these sources may be associated with health complaints (Baliatsas et al., 2015; Bolte et al., 2015), in the present study exposure to ELF was not measured.

Table 2 presents the metrics over the individual arithmetic means (N = 57) over the 0–1 time lags cues of TWA and RCM. The distribution of personal TWA's and RCM's resembles a lognormal distribution. The metrics for the 1–4 h time lags resembled those of the 0–1 h lags.

3.2. Group analysis

Fig. 1 shows the outcomes of the generalized correlation between the actual exposure metrics and the outcome metrics: most important complaint, sum score of complaints, the normalized and the box-cox transformation (Nakagawa and Schielzeth, 2013). From the correlations of all 1855 cues only for one metric the absolute value was between 0.1 and 0.2: “number of peaks above a threshold for the Total RF EMF band at a lag of 0-1 hours before the cue” with sum score of complaints and normalized scores were found. No higher correlation values were found. So at group level no relevant correlations were found.

Further, generalized correlations between 0.8 and 1.0 for time-weighted-average and RCM for Total exposure, uplink and downlink occur. In addition, correlations between 0.4 and 1.0 occur for time-weighted-average and time-above for FM, DECT and Total exposure.

Nevertheless, from the linear mixed model (Supplement B) some exposure metrics were classified as statistically significant. However, the highest percentage of extra explained variance was 1.13% for the metric for time-weighted average downlink for the lag of 0–1 h before the cue for the sum score of complaints, and 1.14% for the normalized scores. Supplement C shows the parameter estimates from the fit of the mixed models along with corresponding significances.

3.3. Within person correlation

We only analysed the 36 participants attributing their most important complaint to a frequency band that we could actually measure with the exposimeter. We analysed on one or two sources of exposure and calculated two metrics per source for the short $(0-1\text{h})$ and the longer lag time (1–4 h), i.e. four correlations per source.

3.4. Sum scores of symptoms

After correction for multiple testing, nine associations in four participants between RF EMF exposure and NSPS remained statistically significant. The nine remaining associations were subsequently adjusted for potential confounders; three associations between NSPS sum scores and WiFi exposure, all in participant #59, remained statistically significant. Fig. 2 shows that in this participant increased WiFi exposure for the short (0–1 h; timeabove) and the longer lag time (1–4 h; timeabove and RCM) was associated with an increase in symptom scores. Fig. 3 shows the associations between the exposure metrics and NSPS sum score. We see that in areas with a few data points the spline displays a wider confidence interval. Further, the confidence interval includes zero for most of the lower values. A very clear effect though is that with an increasing exposure metric in the well determined parts the effects increases too. Furthermore, the effect becomes significant for the higher values, which may explain why for the other four participants the association did not reach significance.

3.5. Most important complaint

After correction for multiple testing, three associations in two participants (#52 and #59) between RF EMF exposure and NSPS remained statistically significant. These associations are plotted in Fig. 4. Two of the three remaining associations (both in participant #59) were subsequently adjusted for potential confounders; both remained statistically significant. Fig. 4 shows that in participant #59 increased WiFi exposure was associated with an increase in the score of the most important complaint. Fig. 5 shows the associations between the exposure metrics and reported severity of the most important complaint.

The association in participant #52 could not be adjusted for potential confounders because there was a poor model fit due to insufficient variation in both exposure and NSPS.

4. Discussion

The main objective of this study was to assess whether in a period of a five days non-specific physical symptoms in persons who report to be sensitive to RF EMF can be explained by objectively measured exposure to RF EMF.

At group level, no statistically significant association was found that is also relevant, as the extra-explained variance is < 1.5%. Associations within persons, corrected for multiple testing and additional confounders, showed to be statistically significant for one person out of the 36 who attributed their most important complaint to a source sending in a frequency band the exposimeter could measure.

4.1. Strengths and weaknesses

As far as we know, this is the first longitudinal population study, measuring personal exposure to RF EMF and analyzing the association with health complaints asked on average 39 times at random cues over five days per person. On average 84% of the cues were answered. The high compliance is in line with compliance reported in the EMA study by Van Wel et al. (2017). Also new is that it was based on multiple exposure metrics, including apart from central tendency also a measure for intermittence, describing the exposure in two sets of time lags: 0–1 h and 1–4 h before the cue. Furthermore, the population consisted of self-declared electrosensitives. All of the above turned out to be typical strengths giving extra outcomes, specifically as the participants could be analysed at the individual level. Typical weaknesses of our approach

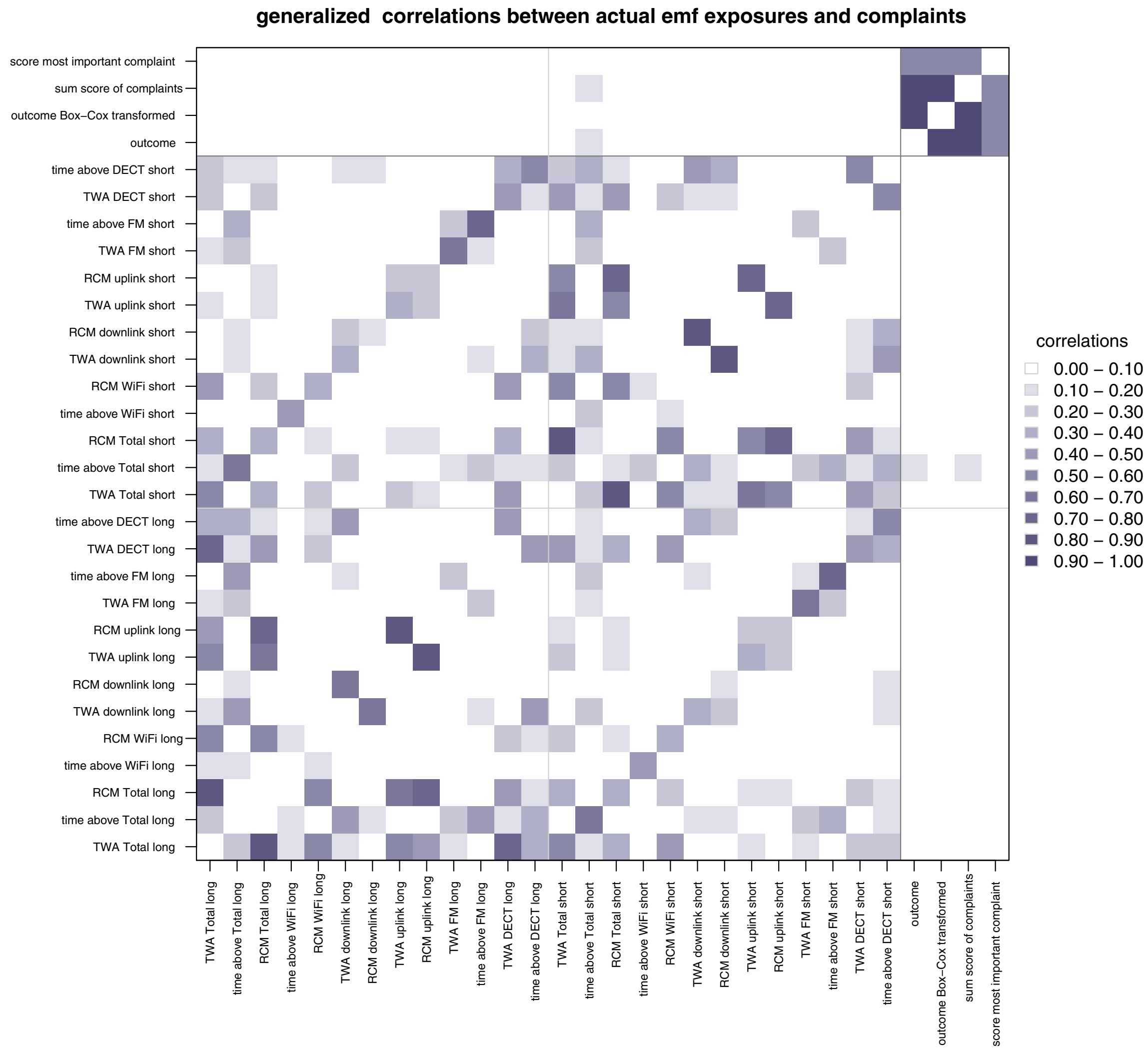
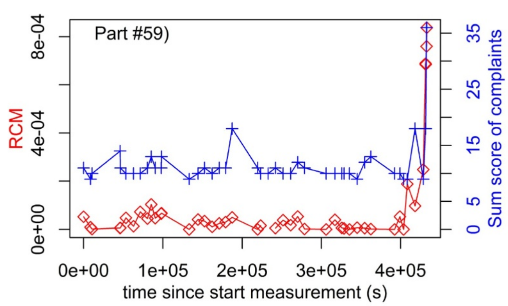


Fig. 1. Generalized correlations over group level cues between actual exposure metrics versus most important complaint, sum score of complaints and transformed complaint metrics: normalized and box-cox transformed score.metric.long and metric.short is the metric calculated for the interval between 1–4 hours, respectively 0–1 hour before the cue.

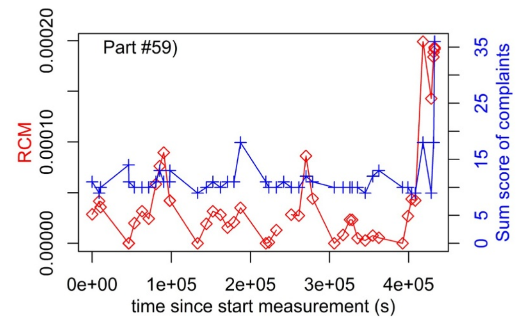
were the type of exposimeter used. Further, we asked the status of complaints at the time of the cue, but we do not know when the onset of the effect started, leaving a chance that a peak in exposure came before the onset of the effect in the given lag.

Selecting a study population of self-declared electrosensitive people attributing their most important health complaint to a measureable RF EMF source increased on the one hand the opportunity to find actual associations at the individual level. Of the 57 participants, 36 provided enough data to be able to analyze. On the other hand, even though 21 people said they attributed their most important complaint to RF EMF, 16 of them could not name the source or frequency band, four of them attributed it to an electric device only generating ELF EMF, and one to a frequency band that could not be measured by the exposimeter. Therefore, over a third of the participants could not be included in the within person analyses. Another weakness is that the ELF magnetic field was not measured while it is a possible confounder as it is correlated to computer use, as is WiFi, and previous research showed an indication of an association between exposure to ELF and NSPS (Bolte et al., 2015).

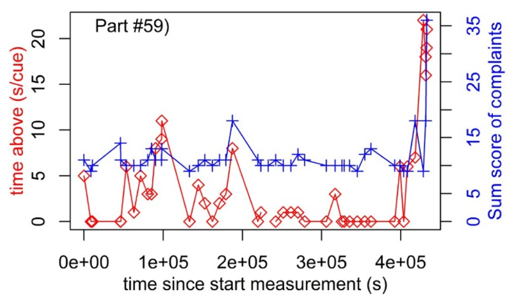
Though measuring personal exposure gives better results than other proxies such as spot measurements or models (Frei et al., 2010), the exposimeter used, EME Spy 121, is known to underestimate the actual exposure, but overestimates exposures to signals with bursts, such as in uplink signals from mobile phones and WiFi appliances (Bolte, 2016). Further, due to uncertainties and biases in the measurements the exposure is on average underestimated (Bolte et al., 2011; Lauer et al., 2012) and protocols or calibration corrections are seldom applied (Bolte, 2016; Röösli et al., 2010). As long as single frequency bands within a person are studied this is not a problem, but in comparing frequency bands or in summing the exposure over a range of frequency bands, this may lead to incorrect total sum exposure and potentially attenuated associations with symptom scores. More important is that the EME Spy 121 cannot measure all relevant exposures to sources used nowadays such as AM radio and HAM radio and WiFi in the 5 GHz band. More importantly, the exposures in the near field as caused by mobile phones and other near-body devices can hardly be measured by any body worn exposimeter (Dürrenberger et al., 2014). Despite the fact that new modelling techniques combining external exposure and internal dose from both far-field and near-field sources are under development, they are not yet widely applied (Roser et al., 2015). Also, potential participants were not willing to wear the exposimeter of this size and weight. Therefore, lighter, more recently developed types measuring more frequency bands with less uncertainties and biases in especially the burst signals are preferred (Bhatt et al., 2016). Although the exposimeters did not have a display that showed RF-EMF exposure, participants might have been aware of their exposure in some situations, for instance while sitting next to a WiFi router, in which case



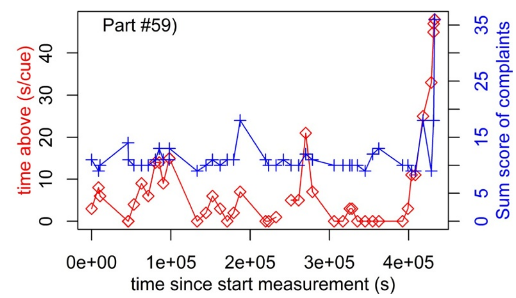
a. WiFi RCM 0-1 hr.



b. WiFi RCM 1-4 hrs*.



c. WiFi timeabove 0-1 hr*.



d. WiFi timeabove 1-4 hrs*.

Fig. 2. Time series plots for different exposure metrics and sum scores of NSPS for associations that remained statistically significant after correction for multiple testing. Associations that remained statistically significant after additional adjustment for confounders are marked with an asterisk. In blue crosses the sum score of NSPS (0-36). In red diamonds the value of the exposure metric.
a. WiFi RCM 0–1 hr.
b. WiFi RCM 1–4 hr*.
c. WiFi timeabove 0–1 hr*.
d. WiFi timeabove 1–4 hr*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

actual exposure and perceived exposure are correlated. However, since perceived and measured exposure were not correlated (see Supplement D), it is unlikely that our results are confounded by perceived exposure.

The electronic diaries with random cues proved to function fine. Two times they dysfunctioned due to programming issues.

The new contributions of our approach consist of performing and comparing group analysis and within persons analysis on self-declared hypersensitive individuals. Furthermore the use of linear mixed models and the corresponding increase in variance explained to judge the influence of the exposure to RF EMF on the group level. For the individual level analyses the combination of penalized splines together with serial correlation seems not to have been used before for analyzing this type of relations.

Even though in the group analysis we found some significant correlations, they were very weak (< 0.2) and therefore not relevant. Also a mixed model approach with the participant as random effect and corrected for confounders did not find any relevant associations between exposure metrics and sum score of complaints or most important

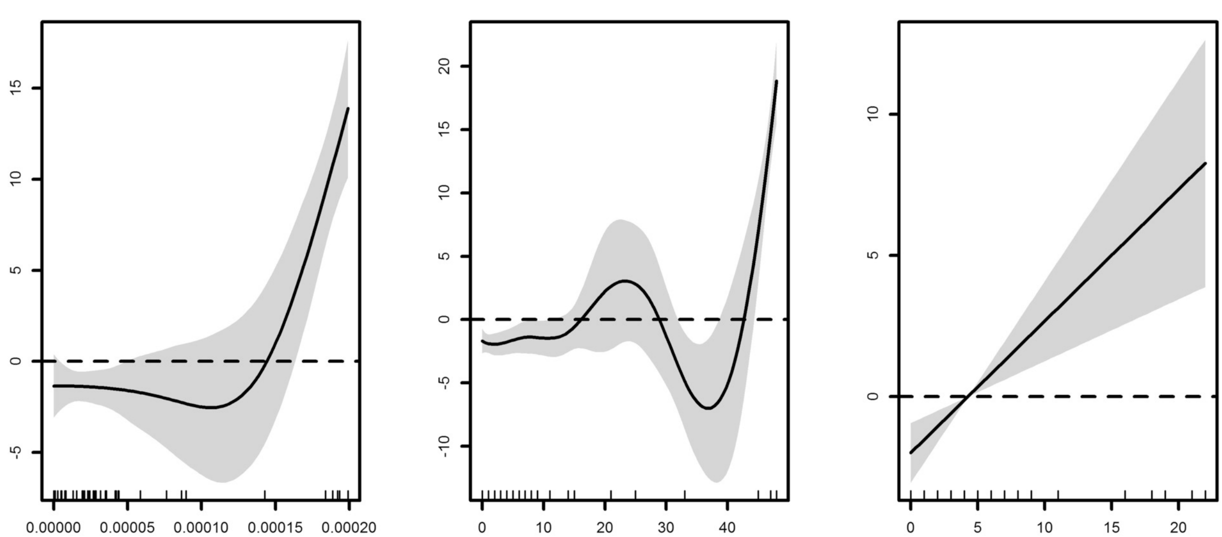
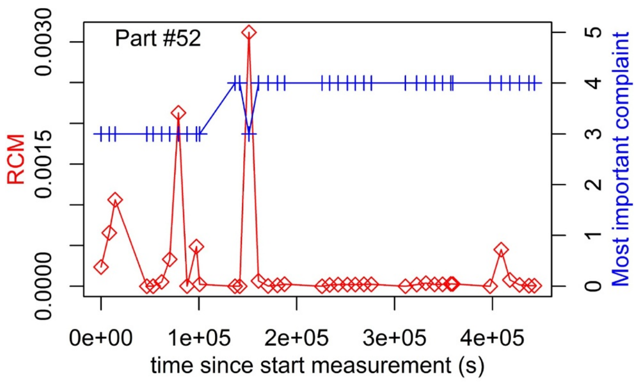
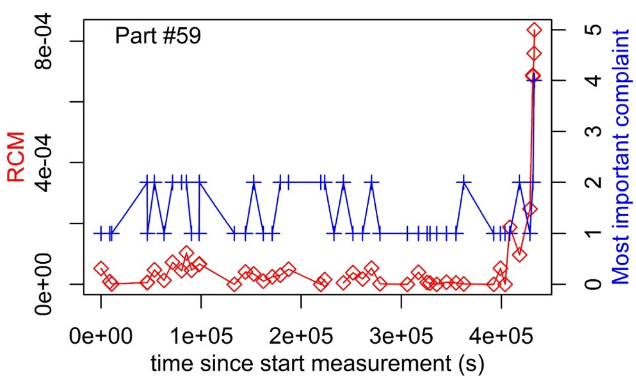


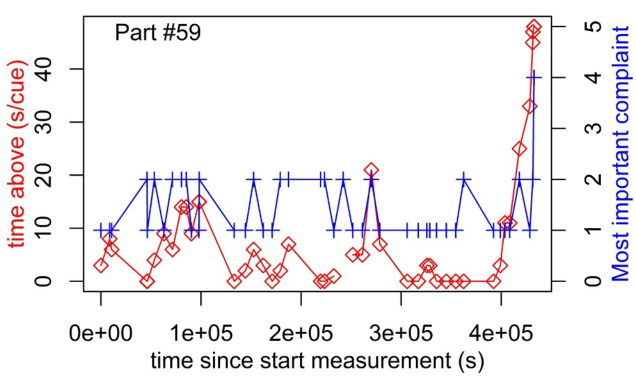
Fig. 3. Confounder adjusted associations for participant #59 between NSPS sum score* and (a) WiFi RCM 1–4 hr lag time; (b) WiFi timeabove 1–4 hr lag time; (c) WiFi timeabove 0–1 hr lag time. The grey area depicts the 95% confidence interval.



a. WiFi RCM 1-4 hrs



b. WiFi RCM 0-1 hr*.



c. WiFi timeabove 1-4 hrs*.

Fig. 4. Time series plots for different exposure metrics and most important complaint scores for associations that remained statistically significant after correction for multiple testing. Associations that remained statistically significant after additional adjustment for confounders are marked with an asterisk. In blue crosses the score of most important complaint (0–4). In red diamonds the value of the exposure metric.
a. WiFi RCM 1–4 hr.
b. WiFi RCM 0–1 hr*.
c. WiFi timeabove 1–4 hr*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

complaint. This outcome is in accordance with systematic evaluations of experimental evidence (Baliatsas et al., 2012a; Röösli and Hug, 2011; Röösli et al., 2010; Rubin et al., 2010) concluding that there is no short-term association between actual exposure and NSPS. It is also in accordance with previous population studies in which groups of participants measured their exposure with exposimeters and filled out questionnaires on their well-being, such as the German MobilEe project, consisting of several cross-sectional studies on mobile phone frequencies and well-being among adults (Thomas et al., 2008a); on children and adolescents and well-being (Thomas et al., 2008b); and behavioural problems (Thomas et al., 2010); and acute symptoms (Heinrich et al., 2010); and chronic well-being (Heinrich et al., 2011); and also a functional analysis on exposure data (Kühnlein et al., 2009). All of the studies were cross-sectional and analysed the measurements at group level and none of them found a significant association between actual exposure and health problems.

As this was a longitudinal approach, we had the opportunity to look into the individual associations between exposure and complaints over time for 36 people attributing their most important complaint to one or two sources the exposimeter was capable of measuring. For the most important complaint and the sum score of NSPS for one participant the 0–1 h and 1–4 h time lags showed an association for different metrics, i.e. the RCM and timeabove. As the significant associations were thus found for both the short and the long time lag, both time lags provide complementary information.

4.2. Interpretation

Table 2 shows that the arithmetic mean over 57 individual mean TWA is 0.399 mW/m^2 which is more than twice the value, 0.180 mW/m^2, as was found in an earlier survey in the Netherlands in 2009–2010 (Bolte and Eikelboom, 2012). As the sampling interval is larger in this study than in the 2009–10 study (36 s vs. 4 s) it was expected that the TWA exposure areas lower as the larger the sampling interval the more maxima will be missed. This is in accordance with findings of a study in Switzerland and Belgium in which the strength of the exposure to RF measured outdoor increased in one year with 20% in Ghent to 57% in Basel (Urbinello et al., 2014). In addition, an Austrian study showed that the indoor median exposure to RF increased from 0.028 mW/m^2 in 2006 to 0.052 mW/m^2 in 2012 (Tomitsch and Dechant, 2015). It is to be expected that the exposure will increase even more as according to the EC (2013), the worldwide mobile traffic alone will be 33 times higher by 2030 compared to 2010.

Though some associations between exposure metrics and the NSPS were statistically significant, we found that the time series did not always support the idea of temporal correlation. This was the case for participant #52. Fig. 4 shows that the negative association with the most important complaint for #52 WiFi for the RCM for the long time lag is due to the lack in variation on the level of the most important complaint, except for a peak in exposure coinciding with a peak in complaints.

Nevertheless, Figs. 2 and 4 also shows that for participant #59 correlations and time series plots indicate that at individual level potential correlations between exposure and NSPS may exist. This visual correlation over time indicates that for #59 an association between exposure to a specific source and NSPS exists. However, it cannot be ruled out that this association is explained by residual confounding due to imperfect control for location or activities. Additionally, even though previous research also found significant within person associations between RCM, timeabove and two other types of most important complaints based on an Arima analysis (Bogers et al., 2018), it is unclear what the mechanism for this association may be. Therefore, the outcomes have to be regarded very prudently.

4.3. Recommendations for future research

We recommend following a different approach in selecting electrosensitive participants for this type of EMA study. Firstly, only people should be included experiencing both variation in exposure and variation in complaints over time, as correlations between time series of exposure and complaints can only be significant and relevant if they vary both. From previous research on microenvironmental exposure (Bolte, 2016; Bolte and Eikelboom, 2012; Frei et al., 2009; Gajsek et al.,

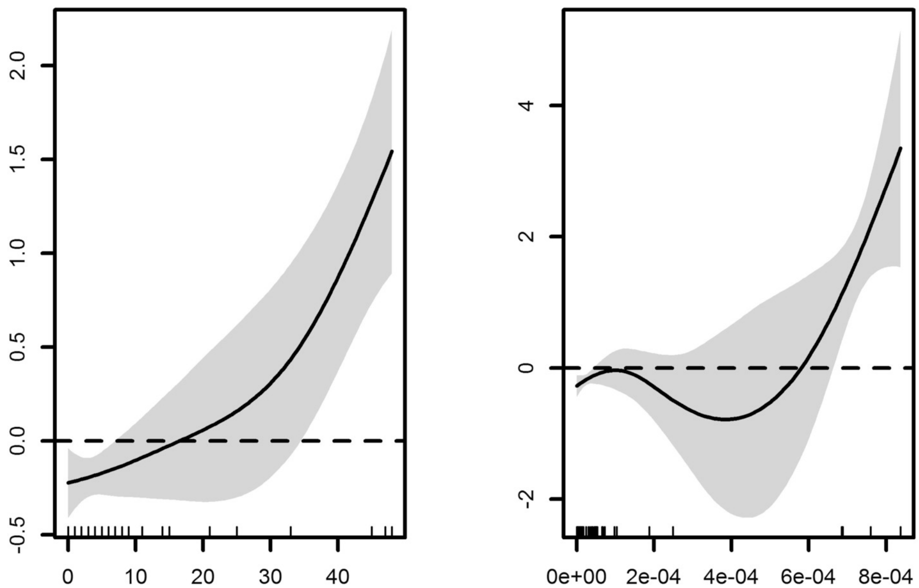


Fig. 5. Confounder adjusted associations for participant #59 between most important complaint (vertical axis) and (a) WiFi timeabove 1–4 hr lag time; (b) WiFi RCM 0–1 hr lag time.

2013; Viel et al., 2009) the exposure differences between different microenvironments have been measured, so from either demographic profiling on behaviour or an initial a priori questionnaire (see Bogers et al., 2018) the exposure contrast can be predicted. In addition, the history on complaints over the week can be asked a priori. Further, participants should only be included if it is thoroughly checked that they attribute their most important complaint to a source truly producing RF EMF and if the exposimeter used is capable of measuring this frequency band.

5. Conclusions

This study did not show relevant associations between exposure to RF EMF and non-specific physical symptoms at group level. At individual level statistically associations between exposure and health complaints were found. As correlations were found for RCM (i.e. intermittency) and timeabove (i.e. peak exposure), this indicates that in contrast to the commonly used TWA metric also the short-term changes in exposure are possibly associated with health complaints. In addition, associations were found for both lag times, but not only concurrently, indicating that the different lag times can provide complementary information and should be looked into. We also conclude that analyses at the individual level can lead to different findings when compared to an analysis at group level.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2019.104948.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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