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Context-sensitive ecological momentary assessments; integrating real-time exposure measurements, data-analytics and health assessment using a smartphone application

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ABSTRACT

Introduction: Modern sensor technology makes it possible to collect vast amounts of environmental, behavioural and health data. These data are often linked to contextual information on for example exposure sources which is separately collected with considerable lag time, leading to complications in assessing transient and/or highly spatially variable environmental exposures. Context-Sensitive Ecological Momentary Assessments[1] (CS-EMAs) could be used to address this. We present a case study using radiofrequency-electromagnetic fields (RF-EMF) exposure as an example for implementing CS-EMA in environmental research.
Methods: Participants were asked to install a custom application on their own smartphone and to wear an RF-EMF exposimeter for 48 h. Questionnaires were triggered by the application based on a continuous data stream from the exposimeter. Triggers were divided into four categories: relative and absolute exposure levels, phone calls, and control condition. After the two days of use participants filled in an evaluation questionnaire.
Results: 74% of all CS-EMAs were completed, with an average time of 31 s to complete a questionnaire once it was opened. Participants reported minimal influence on daily activities. There were no significant differences found between well-being and type of RF-EMF exposure.
Conclusions: We show that a CS-EMA based method could be used in environmental research. Using several examples involving environmental stressors, we discuss both current and future applications of this methodology in studying potential health effects of environmental factors.

1. Introduction

Advances in sensor technology make it possible to log continuous (personal) measurements of various environmental, behavioural and health parameters. Data from these sensors is often stored electronically, allowing it to be viewed and processed later. Such data can subsequently be statistically analysed and linked to contextual information on exposure sources and/or health effects collected via separate electronic means, via questionnaires such as daily diaries, or linkage to registry-based disease or geospatial databases. The downside of this approach is that the separate collection of data hampers full data-integration, which in turn can lead to a considerable lag time between an exposure event and the moment the questionnaire or diary is filled in. This is particularly problematic for assessments of parameters with a transient or variable nature. Examples include environmental exposures that display a high spatial or spatio-temporal variability, or variable or transient health outcomes such as heart-rate variability which could change quickly within a short time frame.

Ecological momentary assessment (EMA) encompasses a range of data collection methodologies used in, amongst others, clinical psychology. Key aspects of EMA are the repeated collection of data under real-world environment conditions, close in time to an event, and at strategically selected moments (Stone and Shiffman, 1994; Shiffman et al., 2008). Depending on the event of interest, triggers for assessments can take place at set intervals, at random moments of the day, at predefined events or following some other sampling scheme. More recently, context-sensitive ecological momentary assessments (CS-EMAs) have been introduced. CS-EMA is an extension of the classic EMA methodology in which a data stream is used to determine the

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[1] CS-EMA: Context-Sensitive Ecological Momentary Assessment.

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moment of assessment (Intille, 2007). For example Dunton et al. (2016) used the smartphone's internal motion sensor to trigger momentary assessments when a predefined amount of physical activity had been detected. The advantages of (CS-)EMA include a better recall due to the short time period between the event of interest and the assessment, and the ability to collect data in the natural, real-life environment of a subject.

The ability to continuously collect and process large amounts of data on environmental parameters, in combination with CS-EMA approaches could be used to identify exposure sources and to explore potential health effects related to environmental factors. We carried out a case study in which we developed a smartphone application capable of processing incoming data in real-time, using exposure levels to trigger momentary assessments. We used exposure to radiofrequency electromagnetic fields (RF-EMFs) as a test case. RF-EMF is highly spatially variable and there have been reports of individuals ascribing a variety of health problems to exposure to RF-EMF (also called electromagnetic hypersensitivity). Frequently reported symptoms include concentration problems, headache, nervousness and fatigue, often occurring within minutes of exposure (Röösli et al., 2004). Previous studies have investigated such effects in controlled laboratory studies. However, these studies have been criticized because usually just one exposure was applied, whereas real-life exposures would represent a mix of different types of frequencies and signal types. Therefore, the use of an EMA design, where the real-life environment is a key aspect, could provide an informative way to study this association. A similar concept has been tried by Bogers et al. (2013), who performed a study where continuous collection of radiofrequency electromagnetic field (RF-EMF) data was combined with a random trigger EMA design. In this study design, the RF-EMF exposure levels did however not trigger the assessments, making it difficult to collect sufficient assessments on less common events.

The aim of the presented study is to test the technical feasibility of CS-EMA by real-time processing of environmental sensor data, the adherence to assessments whose triggers are based on sensor data, and the influence on daily activities of participants using RF-EMF exposure as a test case.

2. Methods

2.1. Study population and protocol

Participants were recruited from the city of Utrecht (the Netherlands) and its surrounding area between May and October 2015. Eligibility criteria included being at least 18 years of age, using a smartphone running the Android operating system, and being able to understand the Dutch language. Participants were recruited via an online portal (www.proefbunny.nl) and obtained a small monetary compensation for their efforts. Two appointments, 48 h apart, were made with each participant. During the first appointment the custom smartphone application (ExpoMDiary) was installed on the participants own smartphone, and the RF-EMF exposimeter was handed out. Participants were instructed to wear the RF-EMF exposimeter between the two appointments and to answer the triggered questionnaires when possible. Each participant was provided with a small bag to carry the RF-EMF exposimeter at the hip level as previously described by Martens et al. (2016). Equipment and data was retrieved during the second appointment and the participant was asked to fill out a short evaluation questionnaire. The evaluation questionnaire consisted of questions regarding the amount of time the devices were carried, the perceived influence on daily activities, and whether the participant had ever linked health problems to RF-EMF exposure. The medical ethical committee of the University Medical Center Utrecht (UMCU) reviewed the study protocol and concluded that further ethical approval was not required.

2.2. RF-EMF exposimeter

An ExpoM - RF exposimeter (Fields at Work GmbH, Switzerland) was used to monitor RF-EMF exposure. The device is capable of simultaneously monitoring 16 different frequency bands, covering the most relevant RF-EMF sources with a high sensitivity (Fields at Work, 2016). Detailed specifications are provided as Supplementary material. Samples were taken once every 8 s and subsequently transmitted to the smartphone application via Bluetooth. Data transmission took less than 100 ms, was performed between the measurement intervals and thus did not interfere with measurements taken. Smartphone and exposimeter had to be within three to four metres of each other to transfer data, depending on the environmental conditions (i.e.: line of sight, smartphone cover).

2.3. ExpoMDiary application

The ExpoMDiary application was written for smartphones running on version 4.0 or later of the Android operating system. If Bluetooth connection to the exposimeter was lost for more than 1 min, the participant received a message asking to check whether the exposimeter was still turned on and within range. If the application was inadvertently turned off, e.g. by turning the smartphone off and back on, it restarts automatically and resumes its functionality. When running, the application would process incoming data and trigger assessments (questionnaires) following the predefined trigger conditions. Relative and absolute exposure events were triggered based on exposimeter data, while phone call events were triggered on call information provided by the participants' smartphone. The condition(s) for triggering the questionnaire, current exposure levels, time to respond and complete the questionnaire, and whether it was completed or not were all recorded.

2.4. Questionnaire trigger conditions

A questionnaire assessment was triggered when one of the primary and all of the secondary conditions were met. Four events were specified as primary conditions: 1) a sudden relative increase in exposure, 2) exposure exceeding an absolute threshold, 3) an incoming or outgoing phone call, or 4) no questionnaires triggered for the past 1.5 h (control event). Sudden relative increase was defined as a tenfold increase in power density (mW/m^2) compared to the moving average of the past half hour. The threshold for the absolute exposure level was set at 10 mW/m^2 (1.94 V/m). This is roughly a quarter of the maximum power density observed by Joseph et al. (40.4 mW/m^2 (3.9 V/m)) during in-situ measurement in the Netherlands, Belgium and Sweden (Joseph et al., 2012). Phone calls are particular events of interest as the phone is typically held close to the head during these events, causing higher exposure levels to the brain. The questionnaire would appear after the phone call was finished.

Secondary conditions were specified as not to overburden the participants. To allow undisturbed sleep, no questionnaires were triggered between 10 pm and 8 am. Minimum wash-out period between answered questionnaires was 45 min. Lastly, no more than 10 questionnaires were triggered on a particular day. Ignored or missed questionnaires did not count towards this total of 10 questionnaires per day. Triggers followed a first come, first serve hierarchy where the first valid trigger would be used, regardless of the previous type or number of triggers during the day.

2.5. Questionnaires

Once triggered, the questionnaire would pop-up on the main screen of the smartphone while simultaneously triggering an audio and vibrate alert. When unanswered, a reminder would pop-up after 5 min. After 10 min the questionnaire would disappear altogether and counted as unanswered.

The questionnaire was specifically designed for this study. The questions were targeted to capture different concepts of stress, wellbeing and symptoms that could vary within a short time frame. The first four questions inquired about stress and wellbeing (i.e.: feeling concerned, stressed, comfortable, tense). These were followed by five symptoms that are frequently reported by persons attributing health effects to RF-EMF exposure (i.e. having concentration difficulties, tiredness, dizziness, headache, heavy feeling in the head). All questions could be scored on a scale of 1 to 6, with 1 being the most and 6 the least favourable feeling. Lastly, two questions asked whether there were any other symptoms the participant was experiencing, and the current location of the participant. Answering options for locations were at home, at work/school, travelling, train station, shopping, sporting, or other. The complete questionnaire can be found in the Supplementary material.

2.6. Statistical analysis

We had a priori defined that our CS-EMA based method would be considered feasible if more than 50% of questionnaires triggered were completed, indicating that it was more likely than not that the current state of health had been assessed. We calculated summary statistics on percentage of completed questionnaires, trigger reasons, and whether participants perceived an influence on daily activities. Wellbeing and symptom-related scores were averaged across the primary condition responsible for triggering the questionnaire. Differences in wellbeing and symptom scores across exposure triggers were tested using non-parametric Kruskal-Wallis tests.

3. Results

We obtained useable data on 34 out of 46 participants. Twelve unusable datasets were excluded due to technical failures in communication between the exposimeter and the smartphone application, resulting in none or few collected questionnaires. These issues were subsequently patched in later versions of the application. The 34 participants were on average 32 years old (range 18–59). There were 15 male (44%) and 19 female (56%) participants. None of the participants reported ever having attributed health related problems to RF-EMF exposure (electromagnetic hypersensitivity). Radiofrequency electromagnetic field exposures were on average 187 μW/m^2 (interquartile range (IQR) 91–235) (Supplemental Table 2).

3.1. Compliance and trigger distribution

Participants received on average 9 questionnaire prompts per day. Of these, on average 74% (IQR 69–79%) were completed per person. Median time between the trigger and start filling in the questionnaire was 28 s (IQR 10–231), and 31 s (IQR 23–41) to complete it after starting. 28 (82%) participants reported minimal influence on their daily activities while 6 (18%) participants reported some influence on their daily activities.

The main trigger reason was a tenfold relative increase in average power density (60.4%), followed by the control condition (28.5%). Only one phone call event triggering a questionnaire occurred. The distribution of trigger reasons for completed questionnaires was similar (Fig. 1).

3.2. Questionnaire outcomes

The results of the nine questions on wellbeing and symptoms are shown in Fig. 2, stratified by the type of exposure that triggered the questionnaire. No significant differences in symptom or well-being scores across the exposure triggers were observed. Other reported symptoms included having a cold, minor back pain, and muscle aches.

4. Discussion

We applied a CS-EMA based method to evaluate the feasibility of using this methodology in environmental health research, using RF-EMF exposure as a test case. A total of 34 complete datasets were obtained with participants completing on average 74% of all assessments and reporting limited influence on daily activities. We encountered several technical challenges that were solved in subsequent patches of the application software, but the high completeness of filled-in questionnaires, together with the low impact on daily lives of participants showed that this approach is feasible to collect CS-EMA information in the general population.

Strengths of our study include that we developed and tested an ecological momentary assessment that uses a real-time exposimeter assessing a highly variable type of environmental stressor which were matched to questions on the most frequently reported health effects ascribed to RF-EMF. To the best of our knowledge, we are the first to apply the approach of a CS-EMA in the context of environmental exposures and potential associated health effects. For our study we installed our application on the smartphone of the participant. One of the main advantages was thus the ability to collect data from the smartphone itself. In this way, one of the most relevant RF-EMF exposure sources could be evaluated as well. The application checked whether a call was made and used this as a trigger event, and in theory any other data stream from a personal smartphone or other sensors could be used as well. For the participant it had the advantage of having to carry just one additional device (the exposimeter) on top of their own smartphone.

The RF-EMF test case is limited by the small dataset and lack of information on current activities and/or behaviour of the participants. The latter are needed when trying to disentangle effects of exposure from those of activity. For example, one could take a relaxing walk in a park that has low RF-EMF exposure. While this could have been included in

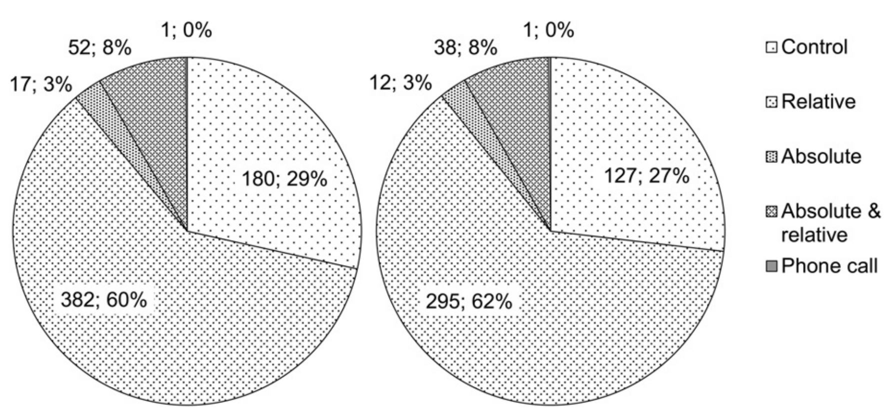

Fig. 1. Distribution of trigger reasons. All triggered questionnaires on the left versus completed questionnaires on the right.

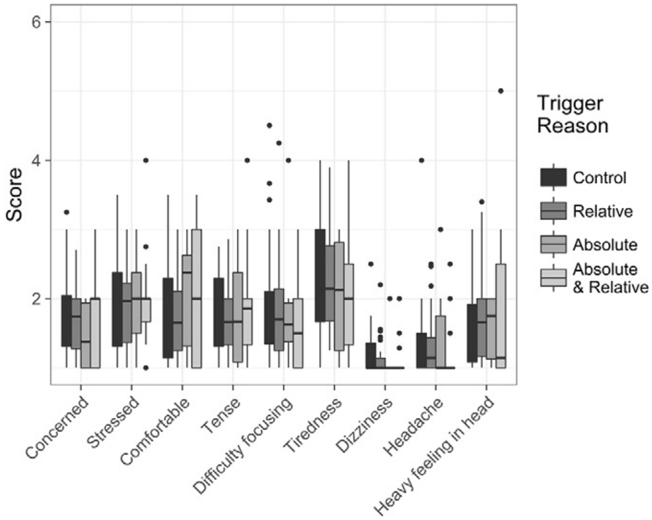

Fig. 2. Results of nine symptom based questions, stratified for trigger reason.

the methodology by adding relevant questions to the assessment or by including an activity and/or GPS tracker, the primary aim of this paper was to discuss the methodological and feasibility aspects of using a CS-EMA based method in environmental health research. The aim of the test case was to illustrate these aspects rather than providing a detailed analysis of the effects of RF-EMF exposure on health. Another limitation lies in the fact that it is difficult to relate any immediate effects and transient symptoms to long term health effects, but even these immediate and transient symptoms can have a negative impact on wellbeing. Related to this point is the fact that any type of exposure would need to cause a very immediate health response in order to be captured by the CS-EMA. This also means that such momentary assessments are possibly not all independent, especially if health effects trigger behavioural changes that in turn affect exposure levels. An example could be a headache due to which a study participant decides to send an email instead of performing a phone call. Future studies should thus carefully evaluate underlying potential mechanisms of the assessed exposures and health outcomes.

4.1. Lessons learnt

Despite being one of the primary conditions specified, a phone call event only once triggered a questionnaire. The reason for this can be found in the secondary conditions we set up. After each completed questionnaire no other questionnaire would happen for 45 min, and if none happened after 90 min the control condition would be triggered. This leaves effectively a 45 min window for a relative, absolute, or phone call event to occur. It turned out that a relative or absolute event would occur more often than a phone call event, each time resetting the 45 min wash-out. This example from the test case shows that it is of great importance to carefully consider the primary and secondary trigger conditions. One possible solution would be to allow for a maximum number of questionnaires per trigger conditions, thus opening up space for other less frequent trigger conditions to actually trigger a questionnaire.

Secondly, we used the own smartphone of a participant to run our application instead of providing a separate device. Benefits included the ability to use information from the participants' own smartphone (i.e.: incoming and outgoing phone calls) and only one additional device to carry around for the participant, the exposimeter. However, this also meant that we had to ensure compatibility between the application and a wide range of Android hardware and software versions. While we were able to patch unforeseen compatibility issues in subsequent versions it meant the loss of some datasets. Clearly, for any future study not addressing RF-EMF exposure, researchers could consider using identical study phones, although this comes at the drawback of an additional device that needs to be carried around by a participant resulting potentially in less adherence to the study protocol.

Lastly, we opted to use a predefined questionnaire where the same questions would always be asked the entire measurement period. We achieved good adherence in our short 48 h measurement period, but for extended measurement periods it might be more difficult to maintain participants' motivation to answer the same questions repeatedly. A possible solution includes alternating questionnaires, or implementing some kind of reward system.

4.2. Future applications

We presented here a test case showing a potential use of CS-EMA methodology in environmental health research, using continuous data streams from both an external sensor and from the smartphone itself. However, this application is not limited to one or two data streams: there are currently a wide range of real-time sensors available, from EMF exposimeters, health sensors (e.g. heart rate), to personal activity trackers. At the same time, the current generation of smartphones provides an affordable and flexible platform to use and analyse data from these sensors. In addition, current smartphones have enough processing power to handle multiple data streams in real-time and various sensors are already built in (e.g.: motion detection, GPS positioning), and standard Bluetooth connectivity allows for easy connection of multiple external sensors. While in our application the data was not streamed directly to study servers for additional analyses such an addition can be easily implemented. For example, the recently developed XMobiSense smartphone application (Goedhart et al., 2015), capable of monitoring mobile phone usage and user behaviour data, was updated to stream data directly to study servers. Further updates will allow modifications to the application protocol without having to return to the research institute.

The creation of an adaptive, dynamic CS-EMA platform capable of interfacing with multiple data streams has the potential to further research into the relation between highly variable environmental exposures and/or variable or transient health outcomes and could also improve data collection and analysis in environmental research. In particular, this includes assessments of immediate reactions to highly variable environmental stressors, disentangling effects from different types of similar exposures (e.g. WiFi vs. GSM exposure), disentangling behaviour and activity effects from exposure effects, or to explore individual sensitivities and thresholds of health reactions. To illustrate this, we provide a few scenarios for using CS-EMA methodology in environmental health research.

4.2.1. Air pollution

Current studies are gathering vast amounts of information on personal air pollution exposure, with a multitude of sensors available to continuously gather data. One such example is the EXPOsOMICS project, where participants carry around a backpack containing air pollution sensors as well as a belt containing a smartphone tracking their location and activity levels (Vineis et al., 2016). This smartphone platform could be adapted to read and interpret the sensor data stream in real-time, allowing for a CS-EMA setup that further investigated acute effects of air pollution exposure. This includes, but is not limited to evaluating individual thresholds of health responses to air pollution levels or to ascertain immediacy or time period until a health response is triggered. A similar concept has been explored by Spira-Cohen et al. (2011), where children carried around a backpack with a variety of samplers. Respiratory symptoms were scored and spirometry measurements performed at set intervals during the day. Using a CS-EMA methodology this can be taken one step further by selecting key moments for symptom scoring and spirometry measurement based on the levels of air pollutants in real-time while also tracking activity using either questions in the assessments or an activity/GPS tracker.

4.2.2. RF-EMF

A natural extension of the CS-EMA approach presented here would be to trigger at specific types of RF-signals that some people report reacting to (e.g. specifically testing WiFi or DECT phone signals). Also, RF-EMF exposure originates from a variety of indoor and outdoor sources, causing complex exposure patterns. Our CS-EMA approach enables linkage of the exposimeter-data to evaluate exposure patterns of interest. When a predefined pattern appears, the questions are not necessarily limited to current wellbeing. Questions regarding details of the current situation, supplemented by GPS coordinates and photographs taken from the surrounding could be included as well. The information could subsequently be used to better interpret observed exposure patterns. This could provide a much more detailed description than a continuous diary as applied by previous researchers (Frei et al., 2009).

4.2.3. Noise

Noise is a widespread environmental factor with high spatial variation and the ability to cause both auditory and non-auditory health effects. There is uncertainty whether specific noise characteristics (e.g. noise frequency spectrum of the sound, intermittency, maximum sound pressure) may be more relevant for health effects rather than average noise levels (Basner et al., 2014). Using a noise sensor in combination with a sophisticated protocol interpreting multiple noise characteristics, health as well as annoyance assessments could be triggered following exposure to any desired combination of noise characteristics. Such an evaluation could be supplemented by obtaining objective stress measurements via skin conductivity and heart rate variability sensors to further elucidate the effects of noise on health.

4.2.4. Odour

Odourants can influence human health via both physical mechanism and via annoyance with large variability in sensitivity to and annoyance from exposure to odours (Schiffman and Williams, 2005). Studies into these effects often use medical records, geographical information systems and paper questionnaires to gather information (Hooiveld et al., 2015). With the continued development of odour sensors, so called electronic noses, we may expect a future odour sensor which can reliably detect odour levels (Deshmukh et al., 2015). The use of such a sensor to gather objective odour data, in combination with a CS-EMA based assessment on annoyance, could help to disentangle effects of annoyance from other mechanisms through which odourants affect human health.

4.2.5. Capturing multiple determinants

Whether the topic of interest is the effect of increased air pollution on lung capacity, high quality details of RF-EMF exposure scenarios, or factors contributing to odour annoyance, the range of applications in environmental research is large and not just limited to a single environmental factor: multiple determinants, ranging from environmental factors to health sensors to geospatial location can all be included to select scenarios in which to assess the current well-being of a study participant.

5. Conclusion

We have shown that it is feasible to use a CS-EMA based method in environmental research, with participants completing on average 74% of all assessments while having only limited influence on daily activities. While there are a number of aspects that need to be taken into account when applying a CS-EMA based method, it shows both current and future potential in studying potential health effects of environmental factors.

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Conflicts of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.envint.2017.03.016.

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