Personal exposure to radio frequency electromagnetic fields and implications for health

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Summary

Background

Exposure to radio frequency electromagnetic fields (RF-EMFs), as produced by mobile phone base stations, broadcast transmitters and cordless phones, has considerably increased over the past 20 years, especially due to the rapid expansion of the mobile phone communication network. Little is known about typical RF-EMF exposure levels and the spatial and temporal variability of RF-EMFs in our environment. Moreover, the contribution of the various exposure sources to total exposure has not been quantified. In general, two types of exposure sources can be distinguished: sources operating close to the body such as personal mobile devices, and environmental far-field sources such as e.g. mobile phone base stations resulting in homogenous whole-body exposure. Only recently have portable exposure meters (exposimeters) become available. These devices are promising for quantifying individual exposure to the most relevant environmental far-field RF-EMF sources during their typical daily life activities, but are not expected to realistically represent exposure from sources operating close to the body because the measurements are heavily influenced by the distance between the emitting device and the exposimeter. In addition, exposimeters are not suitable for use in large-scale epidemiological studies, particularly due to the high costs and the tremendous effort for study participants involved.

Parallel to the increase in RF-EMF exposure, public concern has grown regarding possible adverse health effects of RF-EMFs, in particular concerning non-specific symptoms such as headache. However, to date, only a few epidemiological studies have addressed the possible health effects of environmental RF-EMF exposure. The main reason for that is that assessment of RF-EMF exposure in everyday life is highly challenging. Most epidemiological studies conducted so far were of cross-sectional design, where data on exposure and health are collected at the same point in time. These studies have several drawbacks; in particular they are limited for drawing conclusions about a causal relationship between exposure and health outcomes.

Objectives

The aim of this thesis is to determine the distribution of individual RF-EMF exposure levels in daily life and to identify the factors relevant for the exposure in order to develop an RF-EMF exposure model. In addition, possible non-specific health effects resulting from everyday RF-EMF exposure are examined.

Methods

This thesis was conducted within the framework of the QUALIFEX project (health-related quality of life and radio frequency electromagnetic field exposure: prospective cohort study). QUALIFEX consists of two parts: the exposimeter and main study.

In the exposimeter study, 166 volunteers from the region of Basel carried an exposimeter for one week in order to measure their individual RF-EMF exposure. The participants completed an activity diary and a questionnaire on exposure relevant behaviours. In a validation study, we repeated the exposure measurements of 32 study participants on average 21 weeks after the first measurement. Moreover, spot measurements in the bedroom of the participants and data on exposure levels as perceived by the participants were collected and the geo-coded distance to the closest fixed site transmitter (mobile phone base stations or broadcast transmitter) was computed. The mean residential RF-EMF from fixed site transmitters was computed using a geospatial propagation model. We developed a nonlinear full exposure prediction model by combining the exposimeter measurements, the questionnaire data and the modelled residential RF-EMF.

In the main study, a questionnaire survey investigating potential health effects caused by RF-EMF exposure was conducted in a randomly selected sample of 1375 participants. The questionnaire contained standardised questions on non-specific symptoms (somatic complaints, headache and sleep impairment) and tinnitus. Environmental far-field RF-EMF exposure was assessed using the full exposure prediction model. In order to estimate exposure to close to body sources, objective operator data on mobile phone use as well as self-reported data on mobile and cordless phone use were collected. A follow-up survey was conducted one year after the baseline survey.

Results

In the exposimeter study, the mean RF-EMF exposure to environmental far-field sources for one week was 0.22 V/m. The individual mean values ranged from 0.07 to 0.58 V/m. Mobile phone base stations, mobile phones and cordless phones represent the main contributions to exposure. Radio and television broadcast transmitters, wireless LAN and Tetrapol were shown to be minor exposure sources. Mean values were highest in public transportation vehicles. We identified the following relevant factors for RF-EMF exposure: The modelled RF-EMF at the participants' homes from the geospatial propagation model modified by housing characteristics, ownership of wireless communication devices, and behavioural aspects such as the amount of time spent in public transport. The variance explained (R^2) by the full exposure prediction model was 0.52, and the sensitivity and specificity were 0.56 and 0.95, respectively (cut-off: 90^{th} percentile). We were able to show that the full exposure prediction model can also be used to quantify mean exposure for a period of several months as the model reliably predicted the data of the validation study (sensitivity: 0.67; specificity: 0.96). Concerning other exposure assessment methods used in previous studies, we found that the mean individual exposure measured using exposimeters correlated best with the values derived from the full exposure prediction model and the spot measurements. Individuals' perception of their exposure and geo-coded distance to the closest transmitter turned out to poorly represent personal exposure.

Regarding the health outcomes in the main study, our results do not indicate an impact of RF-EMF exposure in everyday life on somatic complaints, headache, sleep impairment or tinnitus. Neither exposure to environmental far-field sources nor to sources operating close to the body was associated with non-specific symptoms. This finding is in line with a systematic review of the scientific literature on potential health effects of exposure to mobile phone base stations which was conducted in the framework of this thesis. A tendency could be observed in our data that individuals suffered more frequently from non-specific symptoms if they believed to be subject to higher exposure as compared to the general Swiss population.

Conclusions and Outlook

The mean exposure levels measured in our study were well below the current reference values. We were able to demonstrate the feasibility of modelling individual RF-EMF exposure. This makes it possible to assess exposure without expensive and time-consuming individual measurements. The results of our study allow a better interpretation of previous research and a more efficient planning of future epidemiological studies with large populations. We found that crude exposure assessment methods such as calculating the geo-coded distance to the closest fixed site transmitter are not suitable to represent individual exposure levels.

QUALIFEX is the first study to investigate potential unspecific health effects of RF-EMF exposure in daily life using a cohort design. The results allow us to make more robust conclusions in comparison with cross-sectional analyses used in previous research. Moreover, we used objective measures for both environmental far-field and close to body exposure. We did not find indications for a connection between RF-EMF exposure and non-specific symptoms or tinnitus. However, the mean exposure levels were very low and the changes in exposure were small. Our data do not allow us to draw conclusions about possible consequences of higher exposure levels, e.g. values close to the reference values, or effects due to larger exposure changes which may occur in the future. More data on long-term exposure will have to be collected and analysed in order to satisfactorily answer the question whether long-term RF-EMF exposure can cause adverse health effects. This study has successfully evaluated the methods as well as provided a systematic approach which can be used as a guideline for future research on RF-EMF exposure.

Zusammenfassung

Hintergrund

In den letzten 20 Jahren hat die Belastung durch hochfrequente elektromagnetische Felder (HF-EMF), die z.B. von Mobilfunkbasisstationen, Rundfunksendern oder Schnurlostelefonen emittiert werden, in unserer Umwelt massiv zugenommen. Dies ist insbesondere auf die rasante Entwicklung in der Mobiltelekommunikation zurückzuführen. Über die Verteilung der Exposition in der Bevölkerung und über deren örtliche und zeitliche Variabilität ist noch sehr wenig bekannt. Ausserdem ist unbekannt, wie gross der Beitrag der verschiedenen Strahlungsquellen zur Gesamtbelastung ist. Grundsätzlich lassen sich zwei Arten von HF-EMF Quellen unterscheiden: zum einen Geräte, die typischerweise in Körpernähe betrieben werden (Nahfeldquellen), wie z.B. Mobiltelefone, und zum andern Fernfeldquellen, wie z.B. Mobilfunkbasisstationen, die zu einer homogenen Ganzkörperexposition führen. Seit kurzem sind tragbare Messgeräte (Exposimeter) erhältlich, mit denen die individuelle Exposition durch die wichtigsten Fernfeldquellen im Alltag erfasst werden kann. In Bezug auf Nahfeldquellen sind die Messwerte der Exposimeter jedoch wenig aussagekräftig, weil die typische Nutzungsdistanz für diese Geräte viel kleiner ist als die Distanz zum Messgerät. Ausserdem sind Exposimeter für grosse epidemiologische Studien aufgrund der hohen Kosten und dem grossen Aufwand für Studienteilnehmer nicht geeignet.

Mit der Zunahme der HF-EMF Belastung in unserer Umwelt hat auch die Besorgnis in der Bevölkerung im Hinblick auf mögliche Gesundheitsschäden zugenommen, vor allem bezüglich unspezifischer Symptome wie Kopfschmerzen. Bis jetzt wurden zu dieser Frage aber nur sehr wenige epidemiologische Studien durchgeführt. Dies liegt hauptsächlich daran, dass die Abschätzung der Exposition eine grosse Herausforderung darstellt. Die meisten bisherigen Studien waren Querschnittsstudien, bei denen die Daten zu Exposition und Gesundheit zum gleichen Zeitpunkt erhoben wurden. Solche Studien haben verschiedene Nachteile. Insbesondere ist es schwierig, Rückschlüsse auf einen kausalen Zusammenhang zwischen der Exposition und dem Auftreten von Symptomen zu ziehen.

Ziele

Das Ziel dieser Dissertation ist es, die Verteilung der individuellen HF-EMF Expositionen im Alltag zu erfassen und expositionsrelevante Faktoren zu identifizieren. Darauf basierend wird ein HF-EMF Expositionsmodell entwickelt und es werden mögliche unspezifische Gesundheitseffekte durch die alltägliche HF-EMF Exposition untersucht.

Methoden

Diese Dissertation wurde im Rahmen der QUALIFEX-Studie (Gesundheitsbezogene Lebensqualität und Exposition gegenüber HF-EMF: eine prospektive Kohortenstudie) durchgeführt. QUALIFEX besteht aus der Exposimeterstudie und der Hauptstudie.

In der Exposimeterstudie erhielten 166 Freiwillige aus der Region Basel ein Exposimeter und ihre HF-EMF Exposition wurde während einer Woche gemessen. Die Teilnehmer füllten ein Aktivitätstagebuch und einen Fragebogen zu expositionsrelevanten Verhaltensweisen aus. Für eine Validierungsstudie wurde die Messung bei 32 Personen durchschnittlich 21 Wochen nach der Erstmessung wiederholt. Ausserdem wurden Punktmessungen im Schlafzimmer der Teilnehmer durchgeführt, Daten zur selbst eingeschätzten Exposition gesammelt und die georeferenzierte Distanz zur nächsten ortsfesten Sendeanlage (Mobilfunkbasisstation oder Rundfunksender) berechnet. Das durchschnittliche HF-EMF durch ortsfeste Sendeanlagen am Wohnort der Studienteilnehmer wurde anhand eines räumlichen Ausbreitungsmodells berechnet. Durch Kombination der Exposimetermessungen, Fragebogendaten und der durch das Ausbreitungsmodell berechneten Daten wurde ein nicht-lineares Prädiktionsmodell für die persönliche Gesamtexposition entwickelt.

In der Hauptstudie wurde an einer Zufallsstichprobe von 1375 Studienteilnehmern eine Fragebogenuntersuchung zu möglichen Gesundheitseffekten durch die HF-EMF Exposition durchgeführt. Der Fragebogen enthielt standardisierte Fragen zu unspezifischen Symptomen (somatische Beschwerden, Kopfschmerzen und Schlafstörungen) und Tinnitus. Die Belastung gegenüber Fernfeldquellen wurde mit dem Prädiktionsmodell abgeschätzt. Um die Exposition gegenüber Nahfeldquellen zu erfassen, wurden objektive Daten der Mobiltelefon-Netzbetreiber und die eigenen Angaben der Studienteilnehmer zu Mobiltelefon- und Schnurlostelefonnutzung erhoben. Ein Jahr nach der ersten Fragebogenuntersuchung wurde die Befragung in der gleichen Studienpopulation wiederholt.

Resultate

Die Exposition durch HF-EMF Fernfeldquellen während einer Woche betrug in der Exposimeterstudie im Durchschnitt 0.22 V/m. Die niedrigste mittlere Exposition lag bei 0.07 V/m und die höchste bei 0.58 V/m. Die wichtigsten Expositionsquellen waren Mobilfunkbasisstationen, Mobiltelefone und Schnurlostelefone. Der Anteil von Radio- und Fernsehstationen, kabellosem Internet und Tetrapol an der Gesamtexposition war gering. Die höchsten mittleren Expositionen wurden in öffentlichen Verkehrsmitteln gemessen. Für das Prädiktionsmodell wurden die folgenden expositionsrelevant Faktoren identifiziert: Das mittlere mit dem Ausbreitungsmodell berechnete elektromagnetische Feld am Wohnort, modifiziert durch die Eigenschaften des Gebäudes, der Besitz von schnurlosen Kommunikationsgeräten, sowie bestimmte Verhaltenscharakteristiken wie beispielsweise die Zeitdauer, die man in öffentlichen Verkehrsmitteln verbringt. Die erklärte Varianz (R^2) des Prädiktionsmodells war 0.52. Bei Verwendung des 90. Perzentils als Trennpunkt betrug die Sensitivität 0.56 und die Spezifität 0.95. Das Prädiktionsmodell war ungefähr gleich gut, wenn es auf die Daten der Validierungsstudie angewendet wurde (Sensitivität: 0.67, Spezifität: 0.96). Das bedeutet, dass das Modell die Exposition über mehrere Monate vorhersagen kann. In Bezug auf andere Expositionsabschätzungsmethoden, die in früheren Studien eingesetzt wurden, korrelierte die mit dem Exposimeter gemessene persönliche Exposition am besten mit den Werten des Prädiktionsmodells und den Punktmessungen. Es zeigte sich, dass die Selbsteinschätzung und die georeferenzierte Distanz zur nächsten Sendeanlage die persönliche Exposition nur ungenügend widerspiegeln.

Die Resultate der Hauptstudie liefern keinen Hinweis darauf, dass die Exposition gegenüber HF-EMF im Alltag einen Einfluss auf somatische Beschwerden, Kopfschmerzen, Schlafstörungen oder Tinnitus hat. Weder die HF-EMF Exposition durch Fernfeldquellen noch durch Nahfeldquellen war mit dem Auftreten von unspezifischen Symptomen assoziiert. Diese Ergebnisse stehen in Übereinstimmung mit einer systematischen Literaturübersicht zu möglichen Gesundheitseffekten durch die Exposition gegenüber Mobilfunkbasisstationen, die im Rahmen dieser Dissertation durchgeführt wurde. In unseren Studiendaten bestand eine Tendenz, dass Personen häufiger unter unspezifischen Symptomen litten, wenn sie ihre persönliche HF-EMF Belastung im Vergleich zur Schweizer Allgemeinbevölkerung höher einschätzten.

Schlussfolgerungen und Ausblick

Die durchschnittlichen in unserer Studie gemessenen Expositionsniveaus lagen weit unter den geltenden Grenzwerten. Die Studie hat gezeigt, dass die persönliche HF-EMF Exposition modelliert werden kann. Somit ist es möglich, die Exposition ohne teure und aufwändige individuelle Messungen zu erfassen. Zudem erlauben die Resultate unserer Studie eine bessere Interpretation der bisherigen Forschung und eine effizientere Planung zukünftiger epidemiologischer Studien mit grossen Kollektiven. Sie zeigen aber auch, dass einfache Expositionsabschätzungsmethoden, wie das Berechnen der Distanz zur nächsten Sendestation, die individuelle Exposition nicht widerspiegeln können.

QUALIFEX ist die erste Kohortenstudie zur Untersuchung von unspezifischen Gesundheitseffekten durch die HF-EMF Exposition. Verglichen mit früheren Querschnittsstudien erlauben die Resultate unserer Studie robustere Aussagen. Ausserdem wurden in der Studie erstmals objektive Daten zu Fern- und Nahfeldexposition erhoben. Unsere Resultate liefern keine Hinweise für einen Zusammenhang zwischen HF-EMF Exposition und unspezifischen Symptomen oder Tinnitus. Die Expositionsniveaus waren jedoch sehr niedrig und die Veränderungen innerhalb eines Jahres waren gering. Unsere Daten ermöglichen keine Schlussfolgerungen über mögliche Konsequenzen höherer Expositionen, beispielsweise im Bereich der Grenzwerte, oder durch stärkere Expositionsschwankungen, wie sie in Zukunft auftreten könnten. Um die Frage, ob langfristige HF-EMF Belastungen schädliche Gesundheitsauswirkungen haben können, schlüssig beantworten zu können, braucht es noch mehr Daten zu Langzeitexpositionen. In dieser Studie konnten verschiedene Methoden evaluiert werden, und es wurde ein systematischer Ansatz vorgestellt, der als Richtlinie für die zukünftige Forschung im Bereich der HF-EMF Exposition dienen kann.

List of abbreviations and definitions

Abbreviations

95%-CI	95% confidence interval
AM	Amplitude modulation
BMI	Body mass index
CW	Continuous wave
DECT	Digital enhanced cordless telecommunication
EHS	Electromagnetic hypersensitivity
EMF	Electromagnetic field
ESS	Epworth sleepiness scale
FM	Frequency modulation
GSM	Global system for mobile communication
HIT-6	Headache impact test (six questions)
Hz	Hertz
ICNIRP	International Commission on Non-Ionizing Radiation Protection
LTE	Long term evaluation
RF-EMF	Radio frequency electromagnetic field
ROS	Regression on order statistics
SAR	Specific energy absorption rate
SQS	Sleep quality score
UMTS	Universal mobile telecommunications system
Tetrapol	Terrestrial trunked radio police
TDMA	Time division multiple access
TV	Television
V/m	Volt per meter (unit for the electrical field strength)
W/m^2	Watt per square meter (unit for power flux density)
W-LAN	Wireless local area network

Definitions

Downlink	Transmission from mobile phone base station to mobile phone
Exposimeter	Portable exposure meter for measuring RF-EMFs
Fixed site transmitter	Stationary RF-EMF transmitter such as mobile phone base stations or broadcast transmitters (TV or radio)
Nocebo effect	Inverse of the placebo effect, meaning that adverse symptoms occur due to expectations (e.g. due to concerns)
Uplink	Transmission from mobile phone to mobile phone base station

1 Introduction and background

1.1 The electromagnetic spectrum

The frequency spectrum of electromagnetic fields can roughly be divided into non-ionising and ionising radiation (Figure 1-1). The classification is made according to the frequency, i.e. the number of times the wave oscillates per second. Frequency is measured in Hertz (Hz), where 1 Hz corresponds to one oscillation per second. The transition from non-ionising to ionising radiation occurs in the ultraviolet radiation range. Ionising radiation, e.g. x-rays or gamma radiation, is energetic enough to break bonds between molecules, thereby modifying biological components, e.g. inducing DNA damage. Non-ionising radiation is further divided into low frequency and radio frequency electromagnetic fields and infrared, visible and ultraviolet light.

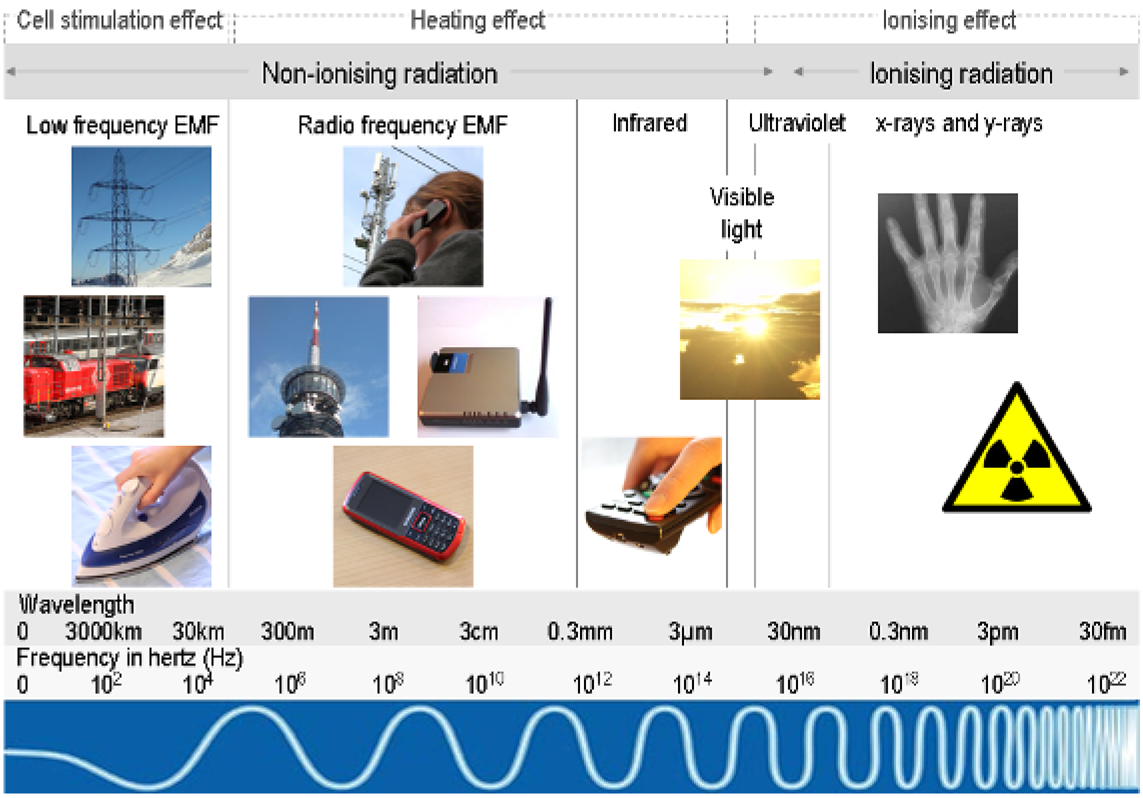

Figure 1-1: The electromagnetic spectrum: sources, wavelengths and frequencies.

Unlike ionising radiation, non-ionising radiation cannot directly modify molecules, but can above certain intensities induce electric fields and currents inside the body and stimulate nerve or muscle tissue (low frequency range) (WHO, 2007), or can be absorbed by biological tissue, thereby producing a heating effect (radio frequency range) (ICNIRP, 1998). Low frequency fields (frequency range: >0 Hz to 100 kHz) occur in the vicinity of power lines and overhead contact lines for railways. They are also produced from all kinds of devices or wires that are operated with electricity, e.g. flat irons or hair-dryers.

1.2 Radio frequency electromagnetic fields: sources and characteristics

Radio frequency electromagnetic fields (RF-EMFs) are used to transmit signals in our environment. The frequency spectrum of RF-EMFs is between 100 kHz and 300 GHz (ICNIRP, 2009b). Typical RF-EMFs emitting sources in our everyday environment and their characteristics are described in Table 1-1.

Table 1-1: Characteristics of typical RF-EMF sources in the everyday environment.

Source		Frequency [MHz]	Wavelength [cm]
FM radio broadcast		88-108	280-340
Television broadcast	TV3	174-223	130-170
	TV4&5	470-830	36-64
Tetrapol		380-400	75-79
Mobile phone	GSM 900	880-915	33-34
	GSM 1800	1710-1785	17-18
	UMTS	1920-1980	15-16
Mobile phone base station	GSM 900	925-960	31-32
	GSM 1800	1805-1880	16-17
	UMTS	2110-2170	14
DECT cordless phone		1880-1900	16
Wireless LAN		2400-2500	12-13

RF radiation is measured as electrical field strength (V/m) or power flux density (W/m^2). These two units can be converted into each other using the formula

$$S = \frac{E^2}{Z_0} \qquad \text{resp.} \qquad E = \sqrt{S \times Z_0}$$

where E represents the electrical field strength in [V/m] and S the power flux density in [W/m^2]. Z_0 is the free space impedance of 377 Ω. In order to be able to transmit information (e.g. audio-visual information), a RF wave is always modulated, i.e. a property of the wave is systematically changing. This can be for example the amplitude (AM) or the frequency (FM) of a wave. There are different medium access methods like time division multiple access (TDMA) that allow several users to share the same frequency. This scheme is for example used by DECT cordless phones and GSM mobile phones and mobile phone base stations. For GSM, one of eight time slots is occupied by one user.

In daily life, we are on the one hand exposed to RF-EMF sources which are operated in close proximity of the body, so-called close to body sources such as mobile and cordless phones. On the other hand, we are exposed to sources that are usually farther away from the body, like mobile phone base stations, broadcast transmitters or base stations of cordless phones. These sources can also be called environmental far-field sources. Close to body sources are generally responsible for highly localised exposure, e.g. in the head area, while exposure is limited to short time periods. Exposure from environmental far-field sources result in a more homogeneous whole-body exposure, which is lower than the maximum exposure due to an operating mobile phone on the head, but occurs usually over prolonged periods of time. Exposure from mobile and cordless phones can be considered both, close to body as well as environmental far-field sources: while the personal mobile and cordless phones are used in close proximity of the body, mobile or cordless phones used by people nearby are generally distant enough to cause an environmental whole-body exposure. Exposure on the head of occasional and regular mobile and cordless phone users is dominated by these close to body sources (Neubauer et al., 2007). Regarding whole-body exposure, the lower but rather continuous environmental far-field exposure might become a relevant exposure contribution.

1.3 RF-EMFs: reference values

The only scientifically accepted effect of RF-EMF exposure on humans is the increase in body temperature caused by high intensity RF-EMF radiation. Below this thermal threshold, no biological mechanism has been established so far (ICNIRP, 2009b; SCENIHR, 2009). The International Commission on Non-Ionizing Radiation Protection (ICNIRP) has published guidelines that limit the exposure to the public in order to prevent heating effects due to RF radiation (ICNIRP, 1998).

The ICNIRP reference values are based on the amount of energy absorbed by the human body, which is called the specific absorption rate (SAR). The SAR is measured in watts per kilogram [W/kg] and depends on the field strength and on the frequency of an exposure source. Generally, the lower the frequency of a RF-EMF the farther it can penetrate biological tissue. The reference values are based on the criterion that the absorbed radiation must never increase the human body temperature by more than 1°C because this can cause interference with various body functions. A higher increase can even lead to internal burns or death due to heat stroke. In order to prevent such heating effects from short-term RF-EMF exposure, the current ICNIRP whole-body SAR limit is 0.08 W/kg for whole-body exposure and 2 W/kg for localised exposures of the head and trunk (ICNIRP, 1998). Since measuring SAR in living persons is impossible, the field strength [V/m] or the power density [W/m^2] measured outside of the human body is used instead. The corresponding reference values are given in Table 1-2.

Table 1-2: Examples of ICNIRP reference values (short-term exposure) and installation limit values (long-term exposure) in Switzerland.

Source		Frequency [MHz]	ICNIRP reference value [V/m]	Installation limit value [V/m]
FM radio & TV broadcast		88-830	28-40	3
Mobile phone base station	GSM 900	925-960	41	4
	GSM 1800	1805-1880	58	6
	UMTS	2110-2170	61	6

The ICNIRP reference values have been adopted by more than 30 countries (Valberg et al., 2007; Grandolfo, 2009). Some countries have instituted reference values that are significantly below the ICNIRP values. In Switzerland, additionally to the ICNIRP reference values for short-term exposures, more restrictive limits called installation limit values have been set for locations where people usually spend a lot of time, like homes, schools or offices (Ordinance relating to Protection from Non-Ionising

Radiation (ONIR)[1]). At these so-called places of sensitive use, the maximum allowed field strength is about 10 times below the ICNIRP reference value (see Table 1-2). These additional limits can be regarded as precautionary measures to ensure that exposure to electromagnetic fields is low at the places of sensitive use. They aim at preventing the public from adverse health effects which might be caused by long-term exposure below the thermal threshold.

1.4 Health effects of RF-EMFs: state of research and open issues

The technical development in the last 20 years has led to a substantial increase of RF-EMF in our environment, especially due to the rapid expansion of the mobile phone communication network (Neubauer et al., 2007). This development has raised public concerns regarding possible health effects of this technology, especially of sources causing involuntary exposure like mobile phone base stations (Hutter et al., 2004; Röösli et al., 2004; Siegrist et al., 2005; Huss and Röösli, 2006; Schreier et al., 2006; Schröttner and Leitgeb, 2008; Blettner et al., 2009). In Switzerland, the general public is most concerned about non-specific symptoms of ill health and reduced quality of life due to EMF exposure, more than about chronic diseases such as cancer (Röösli et al., 2004; Schreier et al., 2006). In 2004, around 5% of the Swiss population attributed non-specific health complaints, in particular headache or sleeping problems, to their EMF exposure in daily life (Schreier et al., 2006). This phenomenon can be described as electromagnetic hypersensitivity (EHS) or idiopathic environmental illness with attribution to electromagnetic fields (IEI-EMF) (Leitgeb and Schröttner, 2003; Rubin et al., 2005; 2006; Röösli, 2008). In addition to developing symptoms due to RF-EMF exposure, EHS individuals often claim to be able to perceive RF-EMF exposure in their daily life environment (Röösli et al., 2004). Population-based studies in other countries across Europe revealed EHS prevalences ranging from 1.5 to 10% (Hillert et al., 2002; Levallois et al., 2002; Eltiti et al., 2007b; Schröttner and Leitgeb, 2008; Berg-Beckhoff et al., 2009; Blettner et al., 2009).

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[1] Verordnung vom 23. Dezember 1999 über den Schutz vor nichtionisierender Strahlung (NISV), SR 814.710.

In response to public concerns, RF-EMF research so far has put a focus on possible effects of exposure to mobile phones or mobile phone base stations on the development of non-specific symptoms. These effects were mostly investigated in human provocation studies performed in laboratories. Usually in such studies different exposure conditions are applied to the same study participant (cross-over design) in two or several sessions, allowing for each participant to act as his/her own control. This eliminates confounding when comparing real exposure situations to sham exposure (no exposure) (dos Santos Silva, 1999). Ideally, the exposure status for the different sessions is randomly assigned and both the study participants and the study investigators do not know the respective exposure status (double-blind design). In 2003, a Dutch provocation study found impaired well-being after UMTS mobile phone base station exposure in EHS and non-EHS individuals (Zwamborn et al., 2003). These results, however, could not be confirmed in a Swiss follow-up study using a more elaborate study design with more than twice as many study participants and applying two different UMTS exposure levels (1 V/m and 10 V/m) (Regel et al., 2006). In general, most of the provocation studies conducted so far failed to provide support for a causal relationship between RF exposure and acute health complaints (Rubin et al., 2005; Röösli, 2008; Rubin et al., 2010). Due to ethical as well as practical reasons, health-effects of prolonged exposure over several weeks or even years cannot be investigated in provocation studies.

Possible effects of long-term environmental RF-EMF exposure on non-specific symptoms in everyday life can only be investigated in epidemiological studies. Only a few epidemiological studies addressing this issue have been conducted so far and no firm conclusions can be drawn from them (Ahlbom et al., 2008; Röösli, 2008; ICNIRP, 2009b). The main reason for this is that RF-EMF exposure assessment is highly challenging (Röösli, 2008; ICNIRP, 2009b). The following methods to assess RF-EMF exposure were used in previous studies: computing the lateral distance of the residence to the closest mobile phone base station (Navarro et al., 2003; Santini et al., 2003), spot measurements in bedrooms of study participants (Hutter et al., 2006; Preece et al., 2007; Berg-Beckhoff et al., 2009; Tomitsch et al., 2010), exposimeter measurements in different microenvironments where a person spends time (Bolte et al., 2008; Joseph et al., 2008) or geospatial modelling of broadcast transmitters or mobile phone base stations (Ha et al., 2007; Neitzke et al., 2007).

However, it is unknown how reliably such exposure assessment methods could represent individual RF-EMF exposure.

Most epidemiological studies performed so far have used a cross-sectional design, where data on health complaints and exposure status are measured at the same point in time (dos Santos Silva, 1999). A major difficulty of cross-sectional studies is that they are limited for drawing conclusions regarding a causal relationship between exposure and health outcome (Seitz et al., 2005). In addition, cross-sectional studies have several other drawbacks: Firstly, when the association between exposure and health outcome differs for those who participate and those who do not participate in a study, spurious exposure-outcome associations can be observed (selection bias). Such spurious associations may also be found when information bias is involved. For example, in a study investigating health effects due to mobile phones, participants suffering from non-specific symptoms may recall their mobile phone use more accurately in comparison to healthy participants because they might have considered the use of mobile phones as a potential cause for their headache (recall bias). Inverse exposure-outcome associations can be expected if people suffering from non-specific symptoms avoid using their mobile phones because they think that mobile phone use might be responsible for their symptoms (avoidance behaviour). Another problem in the field of EMF research is the nocebo effect. It is the inverse of the placebo effect and means that adverse symptoms occur due to expectations (e.g. due to concerns). Several studies have provided evidence for a nocebo effect associated with EMF exposure (Röösli, 2008; Stovner et al., 2008; Rubin et al., 2010).

Only recently have portable measurement devices for measuring individual exposure become available. Unlike stationary devices, portable exposure meters (exposimeters) can record large amounts of personal exposure measurements not only at fixed locations like the home address or the workplace, but also when travelling, and during other activities of daily life. Therefore, they can be used to investigate the spatial and temporal RF-EMF variability. The use of exposimeters is widely recommended in order to characterize the exposure distribution in a certain population (Neubauer et al., 2007; Ahlbom et al., 2008). However, exposimeters are not suitable for use in large-scale epidemiological studies. Exposimeter measurement studies require a large organizational effort and are therefore very expensive. The handling of exposimeters is a demanding and time-consuming task for the study participants, which would likely deter many of them from participating. Study participants might even manipulate the measurements by placing the exposimeter at positions where high RF-EMF exposures are expected thus yielding unreliable results.

Due to the novelty of exposimeters, a thorough investigation of the measuring accuracy of these devices is lacking and several methodological issues are still open. For example, a substantial proportion of exposimeter measurements in everyday life is below the detection limit of the device (0.05 V/m) (Knafl et al., 2008; Thuróczy et al., 2008), which is a challenge for data analysis. When dealing with a large proportion of non-detects, crude approaches like replacing non-detects by a fraction of the detection limit are inappropriate for the calculation of summary statistics (Helsel, 2005; 2006). Moreover, it has not yet been investigated whether exposimeter readings remain stable over time, e.g. over several months. Due to the different characteristics of the various RF-EMF exposure sources, it is unclear whether the exposimeter measures all these sources with the same accuracy. It is for example conceivable that the measurement accuracy for mobile phone base stations depends on the number of active time slots. Last but not least, exposimeters are expected to represent exposure to environmental far-field sources, but not from close to body sources like the personal mobile or cordless phone (Inyang et al., 2008). The reason for that is that measurements during personal phone calls significantly depend on the distance between the emitting device and the exposimeter. Measurements taken during personal mobile and cordless phone use do therefore not reflect exposure of an individual using the phone. It has not yet been investigated to what extent exposimeter readings are affected by measurements that are taken when a study participant uses his/her own mobile or cordless phone.

2 Framework and objectives of this thesis

2.1 The QUALIFEX project

This thesis is part of the QUALIFEX project (health-related quality of life and radio frequency electromagnetic field exposure: prospective cohort study). An overview of the project is given in Figure 2-1. In the first part of QUALIFEX, the exposimeter study, we aimed at determining the RF-EMF exposure distribution in a Swiss population sample using personal exposimeters of the type EME Spy 120 (SATIMO, Courtaboeuf, France, www.satimo.fr). By combining the data collected in the exposimeter study with a separately developed geospatial propagation model, we developed an exposure assessment method, the full exposure prediction model, for the prediction of an individual's exposure level. The full exposure prediction model was then applied in the main study, where we conducted a questionnaire survey to investigate the impact of RF-EMF exposure in daily life on health-related quality of life in a random population sample with a follow-up after one year.

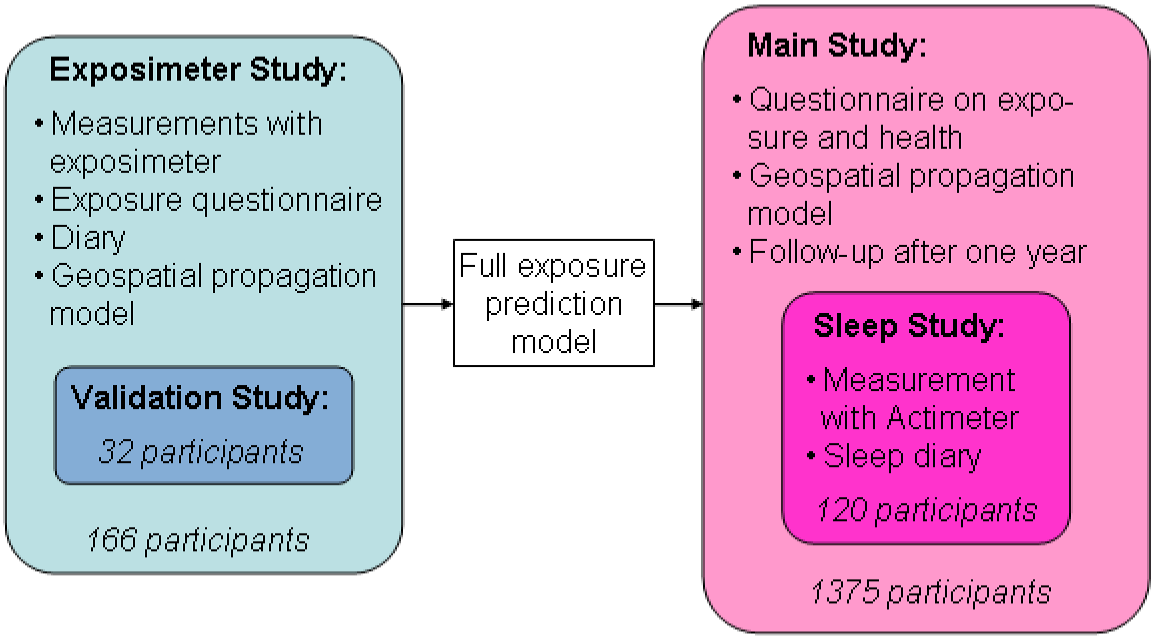

Figure 2-1: Overview of the QUALIFEX project. The sleep study is not part of this thesis. See also www.qualifex.ch.

2.2 Aims of this thesis

Aim 1: *To address, evaluate and solve methodological and practical challenges arising from the use of the personal exposimeter EME Spy 120.*

Figure 2-2: The exposimeter EME Spy 120

Nondetects: One problem we identified was the high proportion of measurements below the detection limit of the EME Spy 120 (0.05 V/m) (Figure 2-2). We evaluated the robust regression on order statistics (ROS) method, in which summary statistics are computed by fitting an assumed distribution to the observed data (Helsel, 2005). The detailed description of this method and the evaluation of the summary statistics of exposimeter measurements obtained with the ROS approach are given in Article 1.

Measuring accuracy: We thoroughly investigated the accuracy of exposimeter measurements. The exposimeter was evaluated in detail in the Laboratory for Electromagnetic Fields and Microwave Electronics at the Swiss Federal Institute of Technology Zürich. The performance of the exposimeter was analyzed in an anechoic chamber, i.e. a room shielded from external RF-EMF by radiation absorbent material. The measuring accuracy of exposimeter readings was evaluated for all measured frequency bands (Table 1-1). Also, different carrier frequencies were tested within the frequency bands: e.g. for the GSM 900 downlink band (925-960 MHz) the measuring accuracy of the exposimeter at 925 MHz, 940 MHz and 960 MHz was evaluated. In addition, different power levels (e.g. 1 V/m, 2 V/m) were tested. We used standard modulated signals for all exposure sources because we discovered that non-modulated continuous wave signals, as used in the past, are not sufficient and only modulated calibration signals should be used for determining the accuracy of exposimeter measurements (Neubauer et al., 2009). Moreover, the isotropy, out-of band response (measurement in the adjacent frequency bands), response to multiple signals and device-dependent variability were investigated in this setting. The results of this evaluation are given in Article 2.

Temporal stability: We evaluated the stability of the exposimeter measurements over time. The Federal Office of Metrology (METAS) performed calibrations with our exposimeters used for the exposimeter study (see Aim 2) in March, June and November 2007 as well as in February 2008 using continuous wave signals (non-modulated) to determine changes in the measurement sensitivity. For each exposimeter and frequency band, temporal calibration factors were determined for the corresponding time period. We performed a sensitivity analysis, where we multiplied each exposimeter measurement obtained in the exposimeter study with the corresponding temporal calibration factor. The mean values obtained with these calibration factors were compared with the mean values obtained without calibration factors. The results of this comparison are presented in Article 3.

Use of sources close to the body: We used the data from the exposimeter study (Aim 2) to investigate the influence of the use of personal mobile and cordless phones on exposimeter measurements. The diary data were used to identify measurements taken when personal phone calls were made. For each individual we calculated two mean values: Firstly, we calculated a mean value by omitting measurements during personal phone use. These mean values correspond to exposure to environmental far-field sources. Secondly, we calculated a mean value including the measurements during personal phone use. The results of the comparison of these two mean values are presented in Article 6.

Aim 2: *To characterise the distribution of personal RF-EMF exposure levels in a Swiss population sample.*

Between April 2007 and February 2008, we collected personal RF-EMF measurements from 166 study participants using personal exposimeters (EME Spy 120). Participants were selected from the city of Basel (Switzerland) and surroundings. Eligibility criteria were age 18 years or above and residency in the study area. The study participants carried an exposimeter during one week and completed a time activity diary, recording their location and the detailed use of cordless and mobile phones every 10 minutes. In order to maximize the range of exposure levels, we recruited 35 volunteers who were expected to have a high residential exposure from mobile phone base stations (n=27) or broadcast transmitters (n=8). The exposimeter measured exposure of 12 frequency bands ranging from radio FM (88-108 MHz) to W-LAN (2400-2500 MHz) every 90 seconds (Table 1-1). For each individual we calculated mean exposure to environmental far-field sources using robust ROS and omitting measurements during personal mobile and cordless phone use. RF-EMF exposure at different locations was calculated from all available measurements for the respective location. To study the reproducibility of exposimeter measurements, we repeated the measurements in 32 participants (validation study). The two weekly measurements were on average 21 weeks (range 3–41 weeks) apart. The results of these analyses are presented in Article 3.

Aim 3: *To develop a method for individual RF-EMF exposure assessment and to evaluate alternative exposure assessment methods*

Geospatial propagation model: Based on a comprehensive database of all fixed site transmitters (mobile phone base stations and broadcast transmitters) for Basel and surrounding communities and a three-dimensional building model of the study area, we developed a geospatial propagation model for RF-EMF from fixed site transmitters. Data on position, transmission direction, antenna types, radiation pattern, transmitter power and number of channels were available for all transmitters. We considered shielding and diffraction by buildings and topography in the model. Figure 2-3 shows the output of the geospatial propagation model for the whole study region. The model was evaluated by calculating Spearman rank correlations and weighted Cohen's kappa statistics between the model predictions and spot measurements at outdoor (street level, in front of windows of participants of the exposimeter study) and indoor (inside bedrooms of the study participants) locations. Article 4 describes the development and validation of the geospatial propagation model.

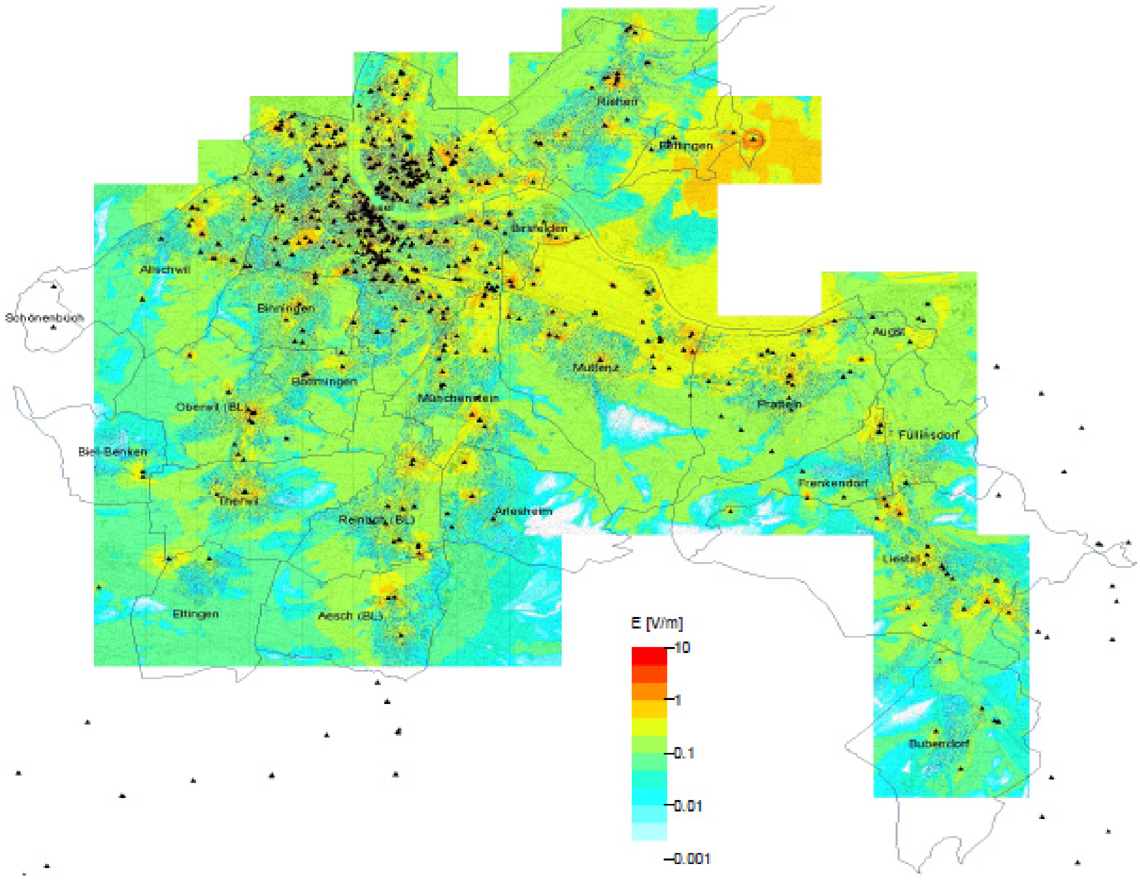

Figure 2-3: Mean field strengths of RF-EMF from fixed site transmitters computed by the geospatial propagation model for the whole study region of Basel and surrounding communities. The black dots represent mobile phone base stations or broadcast transmitters and the colours represent different field strengths.

Full exposure prediction model: For each participant of the exposimeter study, we computed residential RF-EMF from fixed site transmitters by use of the geospatial propagation model. In addition, each participant of the exposimeter study filled in a detailed questionnaire on potentially relevant factors for personal RF-EMF exposure. We developed a full exposure prediction model by combining the exposimeter measurements, the questionnaire data and the modelled residential RF-EMF from the geospatial propagation model. Nonlinear multiple regression models were used in order to identify the most relevant exposure predictors. The model was validated with the second measurements of the persons who took part in the validation study. In Article 5 the development and validation of the exposure prediction model is presented.

Evaluation of alternative exposure assessment methods: Within the exposimeter study, we additionally collected data on alternative exposure assessment methods used in previous research. For each participant, we performed spot measurements in the bedroom using a NARDA SRM-3000 radiation meter, computed the geo-coded distance of the residence to the closest fixed site transmitter and collected data on exposure levels as perceived by the participants. In addition, we modelled residential exposure using the geospatial propagation model and we calculated total environmental far-field exposure using the full exposure prediction model. All these exposure assessment methods were evaluated in terms of their ability to reliably represent personal exposure. We calculated the correlations between the exposure values obtained with the alternative assessment methods and the personal mean values measured by the exposimeters. The exposure assessment methods were additionally evaluated in terms of their applicability in epidemiological studies. The results of these analyses are presented in Article 6.

Aim 4: *To study potential health effects resulting from RF-EMF exposure.*

Systematic review on health effects due to RF-EMF exposure: We conducted a systematic review on the current scientific knowledge on potential health effects of exposure to mobile phone base stations. This review was not done within the framework of the QUALIFEX project. We included provocation studies performed in laboratories as well as epidemiological studies. In addition, we evaluated whether study participants were able to perceive EMF exposure. In Article 7, the methods and results of the systematic review are presented.

Effects of RF-EMF exposure on non-specific symptoms and tinnitus: In the main study of QUALIFEX, we evaluated whether exposure to RF-EMF in everyday life could cause non-specific symptoms or tinnitus. In 2008, we conducted a baseline survey in a random population sample of residents from the region of Basel. We sent out 4000 questionnaires entitled “environment and health”. The questionnaire contained several standardised questions, namely the 24-item von Zerssen list of somatic complaints (von Zerssen, 1976), the six-item Headache Impact Test (HIT-6) (Kosinski et al., 2003), the Epworth Sleepiness Scale ESS for daytime sleepiness (Johns and Hocking, 1997) and a score derived from four standardised questions from the Swiss Health Survey 2007 on general subjective sleep quality (SQS) (Schmitt et al., 2000). A follow-up survey took place one year after the baseline survey. For each participant, we assessed exposure to environmental far-field sources as well as to close to body sources. Regarding environmental far-field sources, we computed residential exposure from fixed site transmitters using the geospatial propagation model (Article 4) and total environmental far-field exposure including behavioural characteristics using the full exposure prediction model (Article 5). In terms of exposure to close to body sources, we asked study participants for informed consent to obtain objective operator data on their mobile phone use over the past 6 months. Moreover, the self-reported use of mobile and cordless phones was assessed. In multivariable regression models adjusted for relevant confounders, we investigated the association between RF-EMF exposure and health outcomes. With regard to the sleep outcomes (ESS and SQS), we conducted a cross-sectional analysis of the baseline survey. The results of this analysis are presented in Article 8. With regard to the somatic complaints (von Zerssen), headache (HIT-6) and tinnitus, we conducted cross-sectional analyses for both, the baseline and the follow-up survey. In addition, we performed a cohort and change analysis for these outcomes. In the cohort analysis, we evaluated the association between exposure level at baseline and the change in health status between the baseline and follow-up survey. In the change analysis, we examined whether the change in exposure between baseline and follow-up resulted in a change in health outcome. The results are given in Article 9.

3 Methodological challenges and evaluation of the EME Spy 120

Article 1: Statistical analysis of personal radiofrequency electromagnetic field measurements with nondetects

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Statistical Analysis of Personal Radiofrequency Electromagnetic Field Measurements With Nondetects

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Exposimeters are increasingly applied in bioelectromagnetic research to determine personal radiofrequency electromagnetic field (RF-EMF) exposure. The main advantages of exposimeter measurements are their convenient handling for study participants and the large amount of personal exposure data, which can be obtained for several RF-EMF sources. However, the large proportion of measurements below the detection limit is a challenge for data analysis. With the robust ROS (regression on order statistics) method, summary statistics can be calculated by fitting an assumed distribution to the observed data. We used a preliminary sample of 109 weekly exposimeter measurements from the QUALIFEX study to compare summary statistics computed by robust ROS with a naïve approach, where values below the detection limit were replaced by the value of the detection limit. For the total RF-EMF exposure, differences between the naïve approach and the robust ROS were moderate for the 90th percentile and the arithmetic mean. However, exposure contributions from minor RF-EMF sources were considerably overestimated with the naïve approach. This results in an underestimation of the exposure range in the population, which may bias the evaluation of potential exposure-response associations. We conclude from our analyses that summary statistics of exposimeter data calculated by robust ROS are more reliable and more informative than estimates based on a naïve approach. Nevertheless, estimates of source-specific medians or even lower percentiles depend on the assumed data distribution and should be considered with caution. Bioelectromagnetics 29:471–478, 2008. © 2008 Wiley-Liss, Inc.

Key words: dosimeter; exposimeter; exposure; detection limit; censored data; radiofrequency electromagnetic fields; mobile phone; cordless phone

INTRODUCTION

Personal exposure measurements are increasingly used in bioelectromagnetic research [Mann et al., 2005; de Seze et al., 2007]. Currently there are two different types of personal, band selective exposure meters available for electric field strength measurements in the radiofrequency (RF) range in the everyday environment: EME SPY 120 (Antennessa, Brest, France) and ESM-140 (Maschek, Kaufering, Germany) [Radon et al., 2006; Knafl et al., 2008]. These meters are sometimes also called exposimeters because they are used for personal exposure monitoring and not for determining the individual dose [Neubauer et al., 2007a]. Exposimeters can be comfortably carried at the upper arm (ESM-140), at the belt or in a backpack (EME SPY 120). The EME SPY measures separately 12 different bands of RF-EMF ranging from radio FM (88–108 MHz) to W-LAN (2.4–2.5 GHz) (Table 1).

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TABLE 1. Description of the Frequency Band of the EME SPY Exposimeter

Band	Frequency (MHz)	Description
FM	88–108	FM radio broadcasting
TV3	174–223	TV broadcasting
Tetrapol	380–400	Mobile communication system for closed groups
TV4/5	470–830	TV broadcasting
GSM900 uplink	880–915	Transmission from handset to base station
GSM900 downlink	925–960	Transmission from base station to handset
GSM1800 uplink	1710–1785	Transmission from handset to base station
GSM1800 downlink	1805–1880	Transmission from base station to handset
DECT	1880–1900	Digital enhanced cordless telecommunications
UMTS uplink	1920–1980	Transmission from handset to base station
UMTS downlink	2110–2170	Transmission from base station to handset
W-LAN	2400–2500	Wireless Local Area Network
Total		Sum of all bands

GSM (global system for mobile communication) and UMTS (universal mobile telecommunications system) refer to mobile communication technology standards.

The ESM-140 measures a smaller number of frequency bands in the GSM, UMTS and W-LAN range. Its measurement sensitivity ranges from 0.01 to 5 V/m.

One limitation of the EME SPY is its lower detection limit of 0.05 V/m (equivalent to a power flux density of 6.7 $\mu W/m^2$ in the far field). Indoor and outdoor measurements showed that a substantial proportion of radiofrequency electromagnetic field (RF-EMF) levels from different communication technologies are below this detection limit in an everyday environment [Bornkessel et al., 2007; Schmid et al., 2007a,b].

Measurements with nondetects are a common phenomenon in environmental research. The worst approach to deal with nondetects is to exclude or delete them. A common approach, usually called naïve approach, is to substitute a fraction of the detection limit for each censored observation. The software of the EME SPY, as an example, set each value below the detection limit to the value of the detection limit (0.05 V/m). However, such substitution produces poor estimates of summary statistics. Correlation or regression analysis may conclude false positive or false negative associations [Helsel, 2005, 2006]. Better results are obtained using non-parametric approaches or methods which assume a given distribution for the nondetects.

Regression on order statistics (ROS) is a method that fits a normal distribution (or log-normal if logs are used) to the observed data. In its robust form the modeled censored values are then combined with the observed values above the detection limit to obtain summary statistics. A full description of the method can be found in Helsel [2005]. By combining the uncensored values with modeled censored values, this method is more resistant to any non-normality errors and may thus be particularly applicable for exposimeter data with a large proportion of censored data. In this article we evaluate ROS in the context of exposimeter measurements taken in the everyday environment.

METHODS

We used a preliminary sample of 109 weekly exposimeter measurements from the QUALIFEX (Health related *quali*ty of life and radio frequency electromagnetic *f*ield *ex*posure: prospective cohort study) study to compare summary statistics computed by robust ROS with a naïve approach. One of the aims of QUALIFEX is to obtain information about the contribution of different sources to the total RF-EMF exposure in a general population sample. During 1 week, volunteers carry an exposimeter and fill in an activity diary. All participants received written information on the study and all subjects gave written consent. The Ethical Committee for Research at Basel approved the study (EK: 38/07).

We recruited six study participants each week, beginning in April 2007, in the urban and suburban area of Basel (Switzerland). They were instructed to carry the EME SPY at the belt or in a backpack when moving. Otherwise (e.g., in the office) they were allowed to place the exposimeter close to the body but not exactly at the same place during the whole week. They recorded their activities as well as their use of mobile and cordless phones in a diary. Furthermore, they filled in a questionnaire about their general exposure relevant behavior and characteristics. In a next working step the exposimeter measurements will be combined with the diary data and the propagation model [Burgi et al., 2008] to develop an exposure assessment method eligible for a large collective. This exposure assessment method will be used in a cohort of 2000 individuals to investigate health related quality of life in relation to RF-EMF exposure.

Note that 17 study participants were selected because they live close to a fixed site transmitter (<100 m from mobile phone base station, or <1 km from a broadcast transmitter). Thus, with respect to these sources our sample presented in this article is not entirely randomly drawn from the population, but intentionally chosen to represent a variety of exposure conditions.

The exposimeter recorded electric field strengths in 12 different bands every 90 s (Table 1). On average we obtained 6330 measurements per person during 1 week. A few technical problems resulted in loss of measurements. Thus, the minimum number of measurements obtained from one individual was 3191 (maximum: 7168).

Antennessa calibrated the EME SPY devices before delivering. Temporal stability of the measurement accuracy of the six exposimeters was investigated in March, June, and November 2007 by the Federal Office of Metrology. Between November and March we observed a maximum negative deviation of -2.3 dB and a maximum positive deviation of $+0.3$ dB in all of the 12 bands from the six devices. According to the manual of the EME SPY, the axial isotropy is between ± 0.3 and ± 3.2 dB for the different frequency bands. Thus, the observed deviation was considered compatible with the measurement uncertainty and no correction was performed.

Our data analysis is based on a preliminary sample of 109 weekly measurements from 109 study participants. We calculated summary statistics for each study participant with a naïve approach and based on the robust ROS method [Helsel and Cohn, 1988]. The naïve approach is used by the EME SPY software. In each frequency band, each value below the detection limit was replaced by the value of the detection limit (6.7 $\mu W/m^2$). The total power flux density over all frequency bands was calculated by adding up the measurements of the 12 bands, omitting all measurements below the detection limit. If at a given time point the measurements from all frequency bands were below the detection limit, EMF SPY set the sum of the 12 frequency bands to the value of the detection limit (6.7 $\mu W/m^2$). For the ROS method we used the robust form of the ''regression on order statistics'' from the package ''NADA'' implemented in the R statistics software (R version 2.5.1, June 27, 2007). We assumed a log-normal distribution for the censored data. Thus, robust ROS fits a linear regression of the logarithms of the data versus their normal scores using data above the detection limit. The obtained regression parameters are used to predict values for each censored observation. The predicted values are re-transformed (exponentiated) and combined with detected observations to compute summary statistics as if no censoring had occurred. In such a way transformation bias can be avoided, which is an issue if one calculates summary statistics on a log scale and re-transforms the obtained parameters. (Transforming data to perform summary statistics and re-transform the result is not equivalent to a summary statistics on the original scale.) In principle, robust ROS could account for multiple detection limits. However, this was not relevant in our context.

We performed no robust ROS calculation if less than 3 values per week were above the detection limit. The lower the number of measurements, the larger is the relative uncertainty of the summary statistics. However, the potential for absolute errors is reduced because the electric field levels have to be very low.

In a second step we calculated the data distribution of the whole study sample, that is, all weekly averages from each frequency band of each study participant. Summary statistics of the naïve weekly averages were obtained with a naïve approach. The ROS method was used to calculate the summary statistics of the weekly averages obtained by robust ROS. In doing so, all estimated weekly averages below 0.265 $\mu W/m^2$ (≤ 0.01 V/m) were considered as censored. This value was determined based on the results of a sensitivity analysis. All calculations were made with values for the power flux density ($\mu W/m^2$). Tabled data were back transformed to electric field strengths (V/m).

RESULTS

The preliminary sample of 109 study participants consists of 58 women and 51 men. The age distribution ranges from 21 years to 78 years with a mean of 44 years. Figure 1 shows exposimeter measurements from one study participant for a period of approximately 6.5 h. All values below the detection limit are drawn on the 0.05 V/m line. Table 2 exemplifies the data distribution, computed with both a naïve approach and with robust ROS, for one study participant. A considerable proportion of the measurements were below the detection limit. In the TV3 and the Tetrapol band all 5362 measurements were below the detection limit, and no robust ROS summary statistic could be calculated. Differences between the naïve and the ROS summary statistics were largest for the lower percentiles. In the radio FM frequency band, for example, only 3.2% of the measurements were above the detection limit. Thus, the naïve 10th percentile is 0.05 V/m whereas the ROS 10th percentile was estimated to be 0.017 V/m. In general, the larger the proportion of nondetects, the larger was the difference between the naïve and the ROS arithmetic mean value. The naïve FM arithmetic mean value is 0.051 V/m; the ROS FM mean value is 0.033 V/m. Even larger differences between the naïve

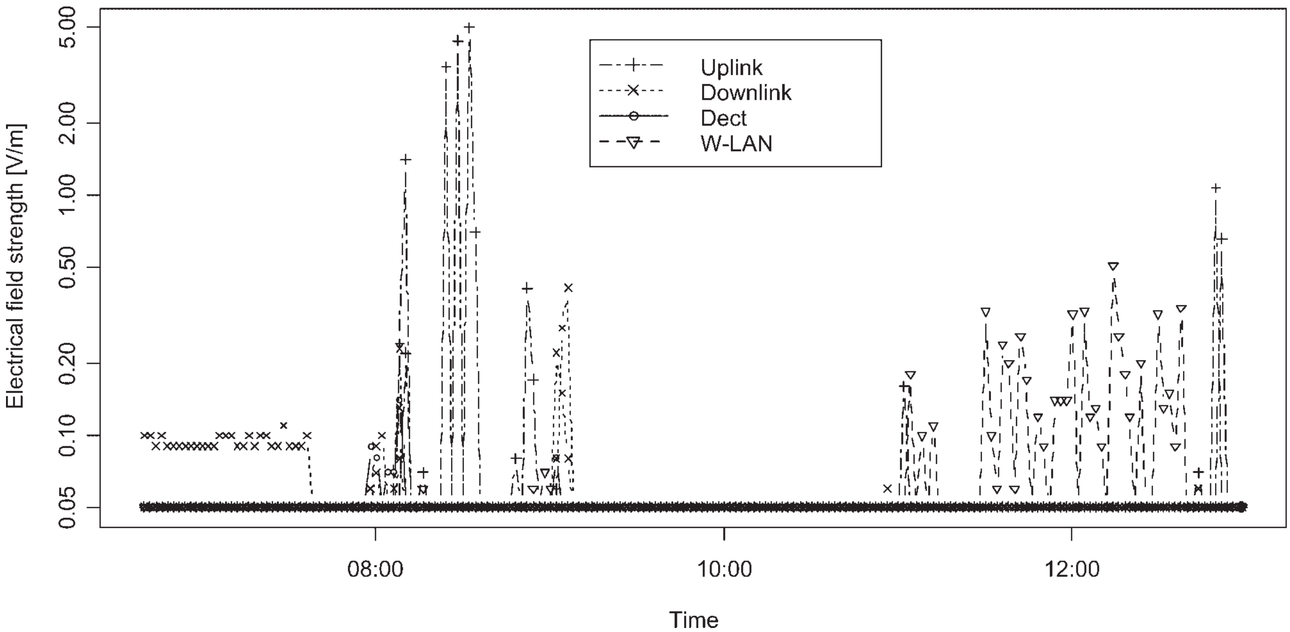

Fig. 1. Example of an exposimeter measurement during 1 day from 6:40 to 13:00. The same symbols are used for all three uplink bands from handset to mobile phone base station (GSM900, GSM1800, or UMTS) and for all three downlink bands from base station to the mobile phone. FM, TV, and Tetrapol are omitted.

TABLE 2. Comparison of the Naïve Summary Statistics With the ROS Summary Statistics for the 5362 Measurements From One Individual

				Percentiles						
Band	Method	Censored	Arithmetic mean	10%	25%	50%	75%	90%	95%	100%
FM	Naïve	5188	0.051	0.050	0.050	0.050	0.050	0.050	0.050	0.090
	ROS	5188	0.033	0.017	0.022	0.028	0.037	0.048	0.055	0.090
TV3	Naïve	5362	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
	ROS	5362	NA[a]	NA	NA	NA	NA	NA	NA	NA
Tetrapol	Naïve	5362	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
	ROS	5362	NA[a]	NA	NA	NA	NA	NA	NA	NA
TV4/5	Naïve	5348	0.051	0.050	0.050	0.050	0.050	0.050	0.050	0.270
	ROS	5348	0.008	0.000	0.000	0.000	0.000	0.002	0.004	0.270
GSM900 uplink	Naïve	5255	0.217	0.050	0.050	0.050	0.050	0.050	0.050	4.998
	ROS	5255	0.211	0.000	0.000	0.000	0.000	0.003	0.012	4.998
GSM900 downlink	Naïve	2625	0.081	0.050	0.050	0.060	0.080	0.110	0.110	1.919
	ROS	2625	0.078	0.028	0.039	0.060	0.080	0.110	0.110	1.919
GSM1800 uplink	Naïve	5310	0.073	0.050	0.050	0.050	0.050	0.050	0.050	1.699
	ROS	5310	0.054	0.000	0.000	0.000	0.000	0.001	0.005	1.699
GSM1800 downlink	Naïve	4476	0.058	0.050	0.050	0.050	0.050	0.060	0.080	0.690
	ROS	4476	0.044	0.014	0.020	0.030	0.045	0.060	0.080	0.690
DECT	Naïve	5178	0.052	0.050	0.050	0.050	0.050	0.050	0.050	0.290
	ROS	5178	0.024	0.003	0.005	0.010	0.018	0.033	0.046	0.290
UMTS uplink	Naïve	5355	0.051	0.050	0.050	0.050	0.050	0.050	0.050	0.270
	ROS	5355	0.006	0.000	0.000	0.000	0.000	0.000	0.001	0.270
UMTS downlink	Naïve	5322	0.051	0.050	0.050	0.050	0.050	0.050	0.050	0.180
	ROS	5322	0.013	0.002	0.003	0.005	0.010	0.018	0.025	0.180
W-LAN	Naïve	5172	0.059	0.050	0.050	0.050	0.050	0.050	0.050	0.600
	ROS	5172	0.035	0.001	0.001	0.004	0.011	0.029	0.051	0.600
Total	Naïve	1978	0.237	0.050	0.050	0.060	0.090	0.118	0.173	4.998
	ROS	1978	0.235	0.024	0.037	0.060	0.090	0.118	0.173	4.998

The number of nondetects are shown in the column "censored." Weekly averages (mean) and different percentiles (10%, 25%, 50%, 75%, 90%, 95%, 100%) of the data distribution are given in V/m.
[a]All values below the detection limit.

approach and ROS were found for other bands with a larger proportion of nondetects such as TV4/5 or UMTS downlink. In contrast, the naïve and the ROS arithmetic mean values for GSM900 uplink are relatively similar, although the proportion of nondetects is high. This is due to the fact that the arithmetic mean is dominated by a few large values, which occurred when participants used their own phone. However, the GSM900 uplink data distribution according to ROS is markedly different than that obtained with the naïve approach. The naïve and ROS mean values for the total RF-EMF are similar. Also, the data distribution is relatively similar due to the high proportion of measurements above the detection limit.

Figure 2 shows normal plots of the distribution of the data from Table 2. From the *y*-scale one can derive that the slope of the diagonal line can vary quite strongly. For instance, radio FM signals were estimated to be more homogenously distributed than GSM900 uplink signals. In the GSM900 uplink band a few right-censored measurements occurred, that is, above the upper detection limit of 5.0 V/m. This can happen if a mobile phone transmits very close to the exposimeter. The figures for GSM900 downlink and for the total field show graphically how ROS estimates the data distribution of the censored values if the data do not follow a log-normal distribution. If the data distribution is left (negative) skewed as can be seen in the radio FM band, a small proportion of the estimated censored values can be above the detection limit. For instance, the ROS 95th percentile of the radio FM band was estimated to be 0.55 V/m whereas the naïve approach yields 0.5 V/m (Table 2). For that reason estimated mean values with ROS can be slightly higher than naïve mean values. In general, however, ROS estimates are lower than naïve estimates.

The proportion of nondetects was large in our sample of 109 weekly measurements (Table 3). The highest proportions of nondedects were found for UMTS uplink (99.9% on average) and for Tetrapol (99%). The lowest proportions were observed for GSM1800 downlink (77% on average) and cordless

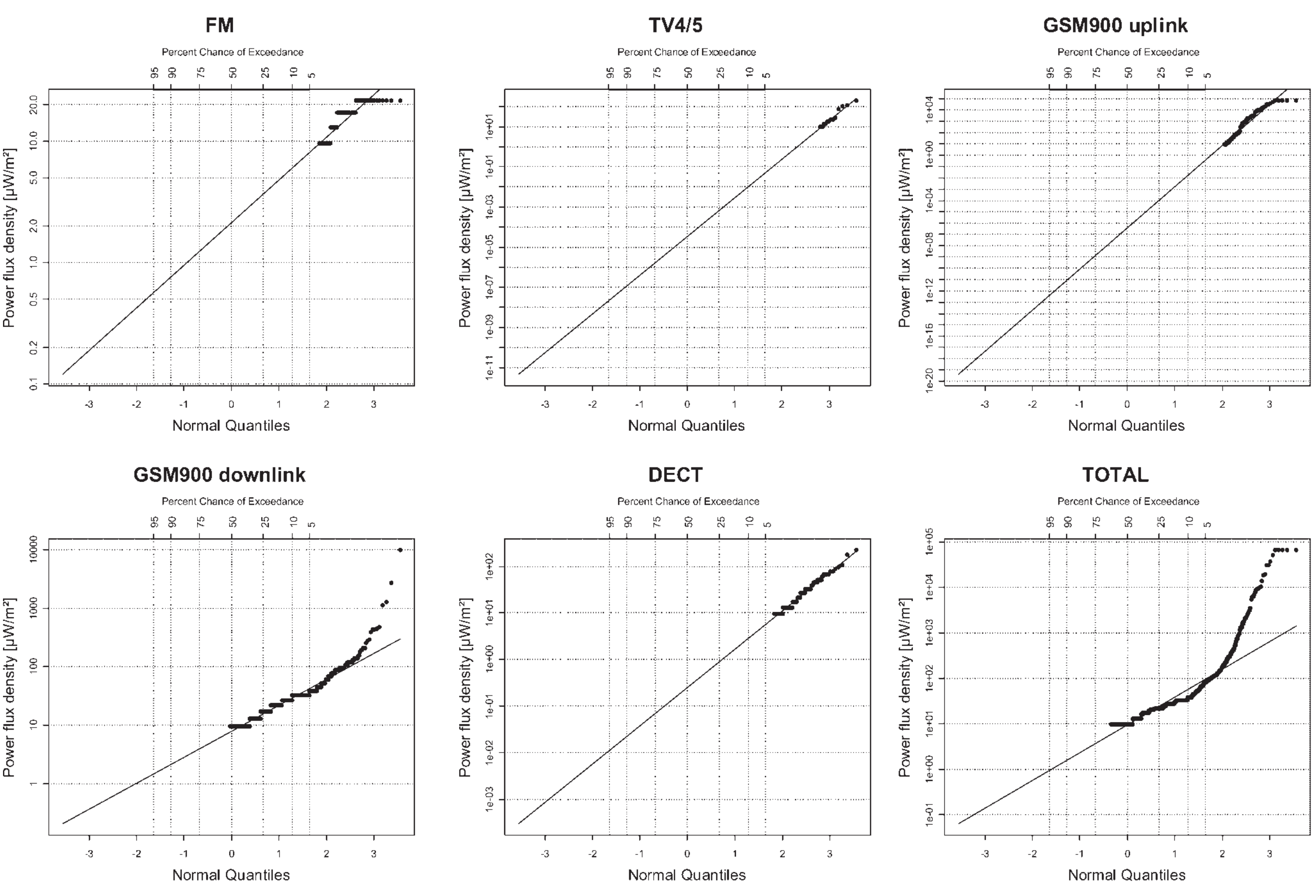

Fig. 2. Normal quantile plots of the data distribution of five frequency bands and the total RF-EMF from the data of Table 2 calculated by robust ROS. Points represent measurements above the detection limit. The diagonal line represents the modeled data distribution of the censored values.

TABLE 3. Overview of the Proportion of Nondetects in Our Data

Band	Minimum (%)	Arithmetic mean (%)
FM	1	88
TV3	23	96
Tetrapol	49	99
TV4/5	5	91
GSM900 uplink	91	99
GSM900 downlink	15	86
GSM1800 uplink	37	96
GSM1800 downlink	4	77
DECT	38	82
UMTS uplink	98	100
UMTS downlink	8	92
W-LAN	41	96
Total	0	45

Minimum refers to the minimum proportion of left censored data in any individual. Mean refers to the mean proportion of left censored data in our sample.

phones (82%). In 45% of the cases the measurements from all frequency bands were below the detection limit (total field).

Table 4 shows the data distribution as well as the mean values of the weekly averages of all study participants for each frequency band. The naïve and ROS sample mean values are similar for all frequency bands except Tetrapol and UMTS uplink. However, for all frequency bands the data distribution of the sample differs between the naïve approach and ROS. For instance, according to the naïve approach one would conclude that 50% of our study sample are exposed to radio FM above 0.05 V/m, whereas the ROS methods yields a median value of 0.02 V/m. Only small differences between the naïve and ROS method are observed for the distribution of the total field strengths in our sample. This is consistent with the observation from Table 2 that the average total field value of an individual is similar for the naïve approach and the ROS method.

DISCUSSION

The main advantages of exposimeter measurements are their convenient handling for study participants and the large amount of personal exposure data that can be obtained from one individual for several RF-EMF sources. However, the large proportion of censored values is a challenge for the data analysis. The problem with inappropriate handling of data below the detection limit is the fact that exposures contribution from minor EMF sources are overestimated, because all

TABLE 4. Data Distribution of Weekly Averages From 109 Study Participants for Different Frequency Bands According to a Naïve Approach and to ROS Method

Band	Method	Arithmetic mean	Minimum	25% quantile	Median	75% quantile	Maximum
FM	Naïve	0.07	0.05	0.05	0.05	0.05	0.41
	ROS	0.06	NA	0.01	0.02	0.05	0.41
TV3	Naïve	0.06	0.05	0.05	0.05	0.05	0.16
	ROS	0.03	NA	NA	NA	0.01	0.16
Tetrapol	Naïve	0.05	0.05	0.05	0.05	0.05	0.12
	ROS	0.01	NA	NA	NA	NA	0.12
TV4/5	Naïve	0.07	0.05	0.05	0.05	0.06	0.26
	ROS	0.05	NA	0.01	0.02	0.04	0.26
GSM900 uplink	Naïve	0.11	0.05	0.06	0.09	0.12	0.25
	ROS	0.10	NA	0.04	0.07	0.10	0.24
GSM900 downlink	Naïve	0.09	0.05	0.06	0.06	0.07	0.33
	ROS	0.08	0.01	0.03	0.04	0.06	0.33
GSM1800 uplink	Naïve	0.08	0.05	0.05	0.06	0.09	0.25
	ROS	0.07	NA	0.02	0.05	0.08	0.25
GSM1800 downlink	Naïve	0.12	0.05	0.06	0.07	0.08	0.52
	ROS	0.11	0.00	0.04	0.05	0.08	0.52
DECT	Naïve	0.12	0.05	0.06	0.09	0.12	0.43
	ROS	0.12	0.01	0.05	0.08	0.12	0.43
UMTS uplink	Naïve	0.05	0.05	0.05	0.05	0.05	0.07
	ROS	0.01	NA	NA	NA	0.00	0.05
UMTS downlink	Naïve	0.06	0.05	0.05	0.05	0.05	0.15
	ROS	0.04	NA	0.01	0.02	0.03	0.14
W-LAN	Naïve	0.06	0.05	0.05	0.05	0.06	0.22
	ROS	0.05	NA	0.01	0.02	0.04	0.23
Total	Naïve	0.23	0.08	0.14	0.19	0.25	0.57
	ROS	0.24	0.08	0.15	0.20	0.26	0.58

All values are given in V/m.

contributions <0.05 V/m are set to 0.05 V/m by the naïve approach. This results in an overestimation of the minimum. Therefore, the exposure range in the population is underestimated and any exposure-response association is biased towards higher values. Moreover, any error in the exposure assessment reduces the statistical power.

Our comparison of the robust ROS method with the naïve approach is limited because there is no possibility of knowing the correct summary statistics for our data. However, it has been demonstrated in many different research areas that summary statistics of data with nondetects can be reliably calculated by the robust ROS method [Helsel, 2005]. If more than 80% of the data are censored, 90th and 95th percentiles can still be reliably estimated with a large dataset. For epidemiological research the 90th and 95th percentile of personal exposure measurements may be a meaningful measure of a threshold above which an individual was exposed at least about 2 or 1 h per day, respectively. In addition, the arithmetic mean exposure value is popular in epidemiology because it corresponds to a cumulative exposure-response model. This is often considered the first choice in the absence of a known biological mechanism, as is the case for RF-EMF below the thermal threshold. Our analysis showed that mean values can be reliably estimated with the robust ROS methods because the arithmetic mean depends more on large values in the sample than on low values. Actually, the naïve approach of the EME SPY yielded values for the total field similar to the robust ROS method. If at a given time point all measurements from all frequency bands are below the detection limit, the EME SPY software uses 0.05 V/m for calculation of the total field strengths. It seems that this assumption is a reasonable estimate of the total, unmeasured, background RF-EMF strengths. Nevertheless, the robust ROS method is expected to provide more reliable estimates. Certainly it should be the method of choice for estimating frequency band specific mean values where we observed larger differences between the naïve and the robust ROS approach.

When performing robust ROS one has to specify a distribution for the data below the detection limit. We assumed a log-normal distribution based on the experience that many environmental data are quasi log-normally distributed. Within the measurement range of the EME SPY (0.05–5 V/m) pooled data from all participants followed the log-normal distribution well. For lower values, a recent measurement campaign of EMF from analogue and digital broadcast transmitters in the intensity range from 5×10^{-4} to 0.2 V/m showed a log-normal distribution [Schubert et al., 2007]. For other RF-EMF sources we did not find published data distributions in the very low intensity range. The strength of the ROS method is its resistance against any errors due to the distribution of the data [Helsel, 2005]. The effect of the assumed distribution on the result is best illustrated with the naïve approach. To assume that all values below the detection limit are equal to the detection limit is the worst conceivable assumption about the data distribution below the detection limit. Nevertheless, the 90th and 95th percentiles and mean values do not differ much between the robust ROS and the naïve approach. However, estimates of the median or even lower percentiles depend on the assumed data distribution if the proportion of nondetects is large. Thus, such estimates should be considered with caution. There might be circumstances where one is interested to know the exposure distribution in a population, even if the information is far from perfect. In this case estimates based on robust ROS are doubtlessly more informative than those based on a naïve approach.

Robust ROS is not the only appropriate method for computing summary statistics of censored data [Singh and Nocerino, 2002]. Maximum likelihood estimations (MLE) are used relatively often [Zhao and Frey, 2004]. MLE estimates the data distribution from the observed values above the detection limit, the proportion of censored data and the mathematical formula for an assumed distribution. In contrast to robust ROS, the summary statistics are based on modeled values only and are thus more vulnerable to deviance from the assumed distribution [Helsel, 2005]. Furthermore, transformation bias is of concern if one deals with log-normally distributed data [Cohn, 1988].

An adequate treating of nondetects is not only required for summary statistics but also for regression analyses, for example, when analyzing the exposimeter measurements with the diary data. Substitution of censored values by a fraction of the detection limit introduces an apparent precision and homogeneity in the data, which does not reflect reality. As a consequence the regression coefficients are biased and the confidence intervals too small [Thompson and Nelson, 2003]. More appropriate approaches are non-parametric analyses, logistic regressions (above vs. below the detection limits) or methods that are derived from the survival analysis. Actually, a data set with values below the detection limits corresponds to a survival data set, where some events have not occurred until the end of the study and thus are censored. Whereas the latter is right-censored, the data with a lower detection limit are left-censored. Left-censored data can be transformed to right-censored data by subtracting each value from the same large constant. After such a "flipping," methods from the survival analyses may be applicable [Helsel, 2005].

The errors introduced by inappropriate handling of censored exposimeter data may appear relatively small compared to the measurement uncertainty of the exposimeters itself [Knafl et al., 2008]. Due to reflection or shielding of the body, uncertainties can reach up to 30 dB for single point measurements [Blas et al., 2007]. A substantial part of this uncertainty may be non-differential, and thus be less of a concern if large amounts of measurements are collected. However, first results of an ongoing study on the reliability of exposimeter reading with respect to real exposure indicate that exposimeters tend to underestimate true exposure due to shielding of the RF-EMF sources by the presence of the body [Neubauer et al., 2007b]. Thus, in our datasets we expect a portion of nondetects due to body shielding which otherwise would have been above the detection limit. Certainly this systematic part of the measurement uncertainty should be taken into account in the interpretation of exposimeter data, although such investigations have not yet been published.

We conclude from our study that robust ROS is an appropriate method to calculate summary statistics of exposimeter data with a large proportion of measurements below the detection limit. Reliable summary statistics are important to accurately estimate the contribution from different RF-EMF sources to the individual as well as to total population exposure.

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Article 2: Reliable assessment of the measurement accuracy of band-selective personal exposure meters: an example study

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Abstract

Body worn RF-EMF personal exposure meters would be the perfect mean to quantify the individual exposure to several different RF-EMF sources together with the exposure pattern. This would allow for the determination of specific features and quantities within the power spectrum arising from the variety of wireless communication and broadcasting services. The requirements on personal exposure meters depend strongly on the biological effect-model that is assumed. In order to test the capabilities of these devices, a general measurement setup and a straight forward measurement protocol is required. Here a novel measurement setup and a measurement protocol are presented for testing personal exposure meters. The whole setup and procedure is tested with an EME SPY 120 device. The performance of the personal exposure meter was analyzed for absolute measurements in an anechoic chamber using modulated signals representing the different services as real signals generated by appropriate testers. Measurement results are evaluated with respect to a root-mean-square detector. Results depend strongly on the carrier frequency and the number of occupied time slots (TDMA based services). Results clearly show that for this device correction factors can only be derived if network configurations at the measurement locations are available. During the test a good feasibility of the measurement procedure and a good performance of the setup could be proven. The presented measurement setup and protocol leads to a higher accuracy in the performance testing of PEMs, which also leads to an improvement in the exposure assessment.

Introduction

The searching of the biological relevance of exposure patterns is still under investigation. In this context different biological effect-models have been proposed, including the root mean square (rms) value E_{rms}, the peak value E_{peak}, the time quantity *t* above a threshold E_{thresh} and the frequency of occurrence of $E > E_{thresh}$ of the electromagnetic field value E. The rms value of the electromagnetic field is the most common used parameter in exposure assessment, which is based on the effect of thermal heating.

In recent years different personal exposure meters have become commercially available, which allow the continuous monitoring of electromagnetic fields. These systems are used for the exposure assessment in epidemiological studies, see e.g. QUEBEB-study (Berg et al., 2006) and QUALIFEX-study (Frei et al., 2009a). In this application area, measurements must be consistent and comparable in terms of measurement uncertainty in order to receive accurate measurement results after calibration. This leads to high requirements for the performance of the measurement device, which are strongly dependent on the used biological effect-model. Up to now no non-thermal biological effect of electromagnetic fields in the radio-frequency (RF) range has been discovered. Therefore, exposure assessment focuses on E_{rms}. In this case the measurement system has to feature linear root-mean-square (rms) detectors, which are insensitive to different signal shapes and are capable to measure multiple signals occurring in the same bands. The measurement results have to be independent of the carrier frequency for signals within the same service band and a high filter selectivity is required in order to encounter a minimum in cross-talk effects. Furthermore, the measurement device should feature an isotropic characteristic and the device dependent variability should be very small.

In order to quantify the performance of personal exposure meter for exposure assessment a reliable and accurate measurement setup and a measurement protocol is required. The performance of the setup and the measurement protocol will be tested by using the EME SPY 120 from Satimo (formerly Antennessa), which is the most commonly used system in epidemiological studies. The gained measurement results will show the potential of the EME SPY 120 to be used for absolute measurements in exposure assessment. The system is evaluated in the frequency range between 380 MHz and 2.5 GHz. The evaluation includes wireless communication services like TETRA, TV broadcast, GSM 900, GSM 1800, DECT, UMTS and communication in the Industrial, Scientific, and Medical Band (ISM) at 2.4 GHz.

The achieved results will also allow for a better interpretation of measurement results collected in experimental and epidemiological studies.

Materials and methods

Reference setup

For the calibration a measurement setup is required that allows to test the performance of a PEM. Therefore, a signal generator must be used that provides signals of different services according to their communication standards. Unfortunately, none of the commercially available exposimeters can be directly connected for calibration which makes it necessary to use a reference measurement device that features a true rms characteristic. Consequently a measurement method which is based on the substitution technique was chosen, where the field strength has been pre-calibrated with the reference system in absence of the exposimeter. Figure 3-1 shows the system diagram for reference measurements. The measurement results of the reference measurement and exposimeter measurement can be directly compared when the same signal settings of the signal generator are used. Therefore, the electric field values of the reference measurements must be calculated from the measured $P_p(f)$ to

$$E_{eff}(f) = \frac{1}{\lambda}\sqrt{\frac{4\pi \cdot P_P(f) \cdot Z_{F0} \cdot L}{G_r(f)}}. \qquad \text{Equation 3-1}$$

Where Z_{F0} is the free space impedance, λ the wavelength, $G_r(f)$ the gain of the receiver antenna and L the losses of the cable and the power divider. As the measurement location an anechoic chamber was chosen. The correct functionality of the whole setup has been tested prior usage with continuous wave signals.

Measurement uncertainty

The measurement uncertainty of the measurement setup and procedure is determined according to (Standardization, 1993). It is given in terms of the expanded uncertainty corresponding to a confidence interval of 95 %. The uncertainty was estimated to be ±2.5 dB. The calculation of the uncertainty includes variations of the antennas phase center, interpolation uncertainties as well as cable calibration and hardware calibration uncertainties.

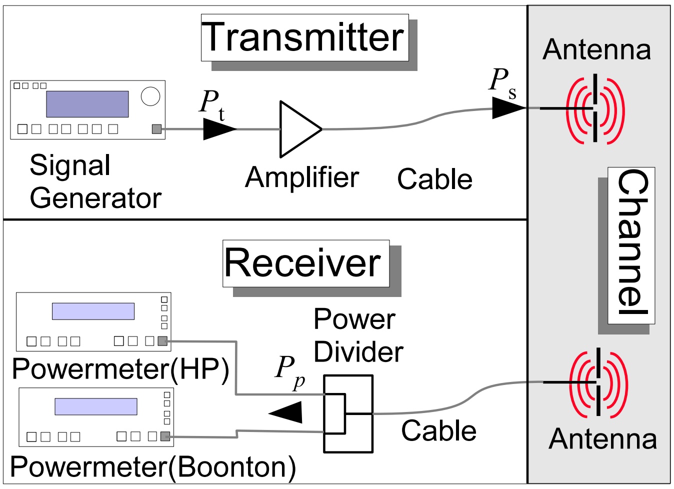

Figure 3-1: System diagram for reference measurement setup. The measurement uncertainty is ±2.5 dB for a confidence interval of 95%.

Characteristics of wireless services

PEMs have to measure different radio frequency (RF) services that are using different modulation schemes. Wireless communication systems like TETRA, GSM 900, GSM 1800 and DECT are using a time division multiple access (TDMA) scheme with different time slots to share the same carrier frequency with multiple users, see (Dunlop et al., 1999) and (Mouly and Pautet, 1992). For all TDMA systems the transmission occurs in bursts, where the rms value has to be accurately measured by the PEM.

UMTS and WLAN 802.11n are using higher modulation standards, like code division multiple access (CDMA) (Walke et al., 2003) and orthogonal frequency division multiple access (OFDM) (Bing, 2007) that features a very high crest factor compared to standard modulated signals like for TV broadcast (Freeman, 2005).

In order to test the performance of the PEM for different services, different signals sources are required.

Measurement equipment

For signal generation the 'SMIQ06B' from Rhode+Schwarz and the 'ESG-3000A' from Agilent were used. Most of the standard signals (e.g. GSM, UMTS, DECT and Bluetooth) can be generated with these two devices. For TV signals the TV pattern generator GV-898+ from PROMAX was used, whereas for WLAN and DECT (operating in the ‘idle-mode’), commercially available equipment was selected for providing calibration signals. The WLAN router P-660HN(-I) from ZyXEL was chosen to test the system for IEEE802.11g standard signals, whereas a classic DECT system from AEG was employed for testing the DECT band for an 'idle mode' signal.

As a reference system, a thermal detector with an HP437B power meter and an HP8481A thermocouple sensor, featuring real rms-characteristic, were used. The lower limit of the dynamic range of this device is around -30 dBm. Signals below this power level were measured with a Boonton 4220 power meter using a diode-detector featuring rms characteristic only for small signal levels. As transmitter and receiver antenna, the 'USLP9143' and the 'USLP9145' (Schwartzbeck – Mess Elektronik e.K., Germany) were used. The antenna features a wide operation bandwidth and covers all frequencies required for testing PEMs. For operating frequencies up to 2 GHz a MCL 'ZHL-10W-2G' amplifier (10 Watt) and for higher frequencies a Nucletudes 'M41.40.45' amplifier (20 Watt) and a MCL 'ZHL-30W-252' amplifier (30 Watt) were installed.

Device under test

Table 3-1 summarizes the technical parameters of the EME SPY 120. The modulation of the different services is also shown, as well as the equipment that was used to generate these signals. The column ‘measurement settings’ gives an overview of the settings the EME SPY 120 was tested for. The anechoic chamber was designed for operating frequencies above 400 MHz. Hence FM and the TV 3 band were not considered in this evaluation. All other services were evaluated at their center frequency, as well as at the upper and lower frequency bounds, except for the TV 4-5 band, TETRA and the DECT service. The TV band was evaluated for seven carrier frequencies due to the wide frequency range and for TETRA and DECT the evaluation was restricted to the center frequency due to their very small occupied frequency range. Measurements were performed for different power levels and for TDMA based services different slot configurations were chosen. The exposimeter was evaluated in vertical and horizontal orientation. If not other stated the exposimeter was positioned in vertical orientation, facing the transmitter antenna.

Table 3-1: Technical parameters of the measurement device and measurement setup

Service	Characteristics EME SPY		Characteristics of services		Used equipment	Measurement settings		
	Frequency range [MHz]	Detection limit [V/m]	Modulation	Channel access scheme	Signal generator	E_{eff} [V/m]	Frequency [MHz]	Tested slot configurations (TDMA)
FM	88-108	0.05 - 5	FM[1]	-	-	-	-	-
TV 3	174-223	0.05 - 5	FM/AM[2]	-	-	-	-	-
TETRA	380-400	0.05 - 5	π/4-DQPSK[3]	4-TDMA	R&S - SIMIQ06B	~0.01 - ~5.5	390	1; 2; 4
TV 4-5	470-830	0.05 - 5	FM/AM	-	Promax - GV-898+	~0.01 - ~5.5	470, 500, 600, 650, 700,800,830	-
GSM 900tx	880-915	0.05 - 5	GMSK[4]	8-TDMA	R&S - SIMIQ06B	~0.01 - ~5.5	880, 900, 915	1; 2; 4; 8
GSM 900rx	925-960	0.05 - 5	GMSK	8-TDMA	R&S - SIMIQ06B	~0.01 - ~5.5	925, 940, 960	1; 2; 4; 8
GSM 1800tx	1710-1785	0.05 - 5	GMSK	8-TDMA	R&S - SIMIQ06B	~0.01 - ~5.5	1710, 1750, 1780	1; 2; 4; 8
GSM 1800rx	1805-1880	0.05 - 5	GMSK	8-TDMA	R&S - SIMIQ06B	~0.01 - ~5.5	1800, 1840, 1880	1; 2; 4; 8
DECT	1880-1900	0.05 - 5	GFSK[5]	24-TDMA	R&S - SIMIQ06B + AEG device	~0.01 - ~5.5	1890	1; 2; 4; 12
UMTStx	1920-1980	0.05 - 5	QPSK[6]	CDMA	R&S - SIMIQ06B + Agilent ESG-3000A	~0.01 - ~5.5	1920, 1950, 1980	-
UMTSrx	2110-2170	0.05 - 5	QPSK	CDMA	R&S - SIMIQ06B + Agilent ESG-3000A	~0.01 - ~5.5	2110, 2140, 2170	-
ISM	2400-2500	0.05 - 5	64 QAM[7]	OFDM	Zyxel - P-660HN(-I)	~0.01 - ~5.5	2412, 2437, 2472	-

[1] Frequency modulation
[2] Amplitude modulation
[3] Differential quadratur phase shift keying
[4] Gaussian mono shift keying
[5] Gaussian frequency shift keying
[6] Quadrature phase shift keying
[7] Quadrature amplitude modulation

Two EME SPY 120 devices were evaluated in order to analyze the device dependent variability. The devices are indicated by the capital letters ‘A’ and ‘B’.

Evaluation of measurement results

For the analysis the measured electric field strength $E_{EME\ SPY\ 120}$ of the exposimeter is plotted versus the reference field strength $E_{reference}$ in logarithmic scale. The average deviation e(f) to the reference is also summarized in a table. *e(f)* is calculated for five different field levels per configuration:

$$e(f) = \frac{1}{5}\sum_{i=1}^{5} E_{i,EME\_SPY}(f) - E_{i,reference}(f)\,. \qquad \text{Equation 3-2}$$

Please note that for the calculation of *e(f)* only field levels below the upper limit of the dynamic range of the DUT were chosen. Thus the DUT was always operating in the linear range. The following measurement results have been received with the exposimeter indicated with an ‘A’.

Measurement Results

TETRA

Figure 3-2 summarizes the results for TETRA. The numbers in the brackets behind the carrier frequency indicate which of the four time slots were active. Please note that the numbering starts with 0. The graph shows a good linear behavior of the signal detector for different operating frequencies and for different occupied time slots. However, the variation of the measurement results for different operating frequencies and different time slots is significant and varies between -0.3 dB and 8.8 dB to the reference line (see also Table 3-2). The results depend strongly on the number of occupied time slots. The less time slots are in use, the higher the overestimation of the electromagnetic fields. The axial isotropy for vertical and horizontal orientation of the exposimeter is 0.6 dB.

TV-bands 4 and 5

Figure 3-3 shows the measurement results for the TV-bands 4 and 5. The results show a good linear behavior of the signal detector for different operating frequencies. However, the variation of the measurement results for different operating frequencies from the reference is significant and varies between -2 dB and -14 dB. The axial isotropy for vertical and horizontal orientation of the exposimeter is 2.5 dB.

Table 3-2: Average deviation e(f) of the measured electric field of device A to the reference measurement for a vertical orientation of the DUT.

Tetra	380 MHz	390 MHz	400 MHz
A - 4 Slots	1.99 dB	1.01 dB	-0.31 dB
A - 3 Slots	4.26 dB	2.89 dB	1.27 dB
A - 2 Slots	5.83 dB	4.52 dB	2.98 dB
A - 1 Slot	8.77 dB	7.46 dB	6 dB
TV 4-5	470 MHz	650 MHz	830 MHz
A	-5.9 dB	-4.5 dB	-14.5 dB
GSM 900tx	880 MHz	900 MHz	915 MHz
A - 8 Slots	-1.08 dB	0.85 dB	0.06 dB
A - 4 Slots	1.69 dB	3.44 dB	2.77 dB
A - 2 Slots	4.47 dB	6.3 dB	5.58 dB
A - 1 Slot	7.04 dB	8.95 dB	8.26 dB
GSM 900rx	925 MHz	940 MHz	960 MHz
A	-4.06 dB	-1.46 dB	-0.16 dB
GSM 1800tx	1710 MHz	1750 MHz	1780 MHz
A - 8 Slots	2.06 dB	3.05 dB	2.21 dB
A - 4 Slots	4.72 dB	5.84 dB	5.28 dB
A - 2 Slots	7.41 dB	8.57 dB	8.12 dB
A - 1 Slot	10.05 dB	10.8 dB	10.41 dB
GSM 1800rx	1800 MHz	1840 MHz	1880 MHz
A	0.72 dB	1.21 dB	1.59 dB
DECT	-	1890 MHz	-
A - 12 Slots		7.82 dB	
A - 4 Slots		11 dB	
A - 2 Slots		11.9 dB	
A - 1 Slot		12 dB	
UMTStx	1920 MHz	1950 MHz	1980 MHz
A	3.63 dB	1.38 dB	-2.84 dB
UMTSrx	2110 MHz	2140 MHz	2170 MHz
A	1.57 dB	0.97 dB	-0.24 dB
WLAN	2412 MHz	2437 MHz	2472 MHz
A	-0.72 dB	-3.6 dB	-5.29 dB

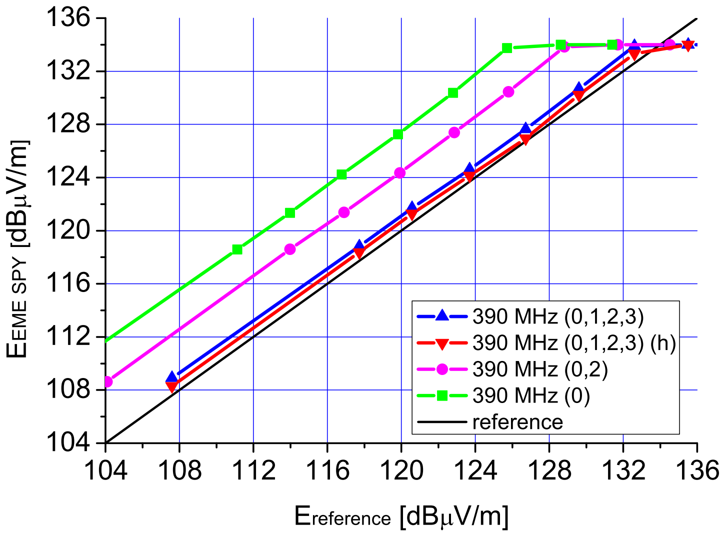

Figure 3-2: Comparison of measured electromagnetic fields in the TETRA band for different slot configurations with EME SPY 120 and a RMS reference system. The abbreviation 'h' indicates a horizontal orientation of the exposimeter. The numbers in the brackets indicate which time slots were active.

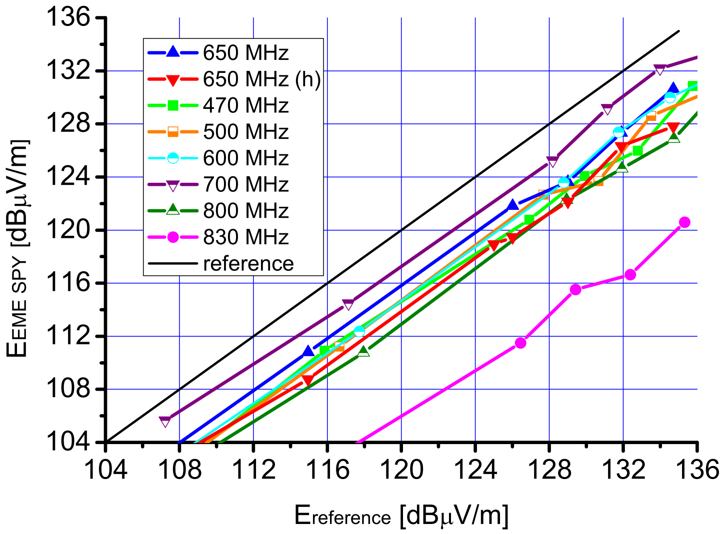

Figure 3-3: Comparison of measured electromagnetic fields in the TV band 4-5 with EME SPY 120 and a RMS reference system. The abbreviation 'h' indicates a horizontal orientation of the exposimeter

GSM 900 uplink

Table 3-2 summarizes the results for GSM 900tx for different carrier frequencies and different slot configurations. The average deviation *e(f)* is calculated according to Equation 2. The DUT showed a good linear behavior of the signal detector for different operating frequencies and for different occupied time slots. The variation of the measurement results for different operating frequencies and different time slots is significant and varies between 0.1 dB and 9 dB with respect to the reference line. The results depend strongly on the number of occupied time slots. The fewer time slots are in use, the higher the overestimation of the electromagnetic fields. The difference between vertical and horizontal orientation of the DUT is 0.85 dB.

GSM 900 downlink

Using fewer than 8 time slots in the GSMrx band leads to a non-detection. Thus analysis is restricted to 8 time slots. Table 3-2 summarizes the results for the GSM 900rx. The behavior of the signal detector was linear for all operating frequencies. An offset to the reference curve was observed for different operating frequencies, varying between -0.2 dB and -4 dB. For the axial isotropy a difference of 5 dB could be observed.

GSM 1800 uplink

The results for GSM 1800tx are summarized in Table 3-2. The exposimeter shows similar behavior to GSM 900tx. The signal detector operates linearly for different frequencies and for different time slots. The variation of the detected signals depends strongly on the number of occupied time slots. The maximum deviation to the reference curve is 10.8 dB for a one slot configuration at 1750 MHz. The difference between vertical and horizontal orientation is 2 dB.

GSM 1800 downlink

A GSM signal with less than 8 time slots was not detected by the exposimeter. Thus further analysis was restricted to 8 time slots. Table 3-2 shows the results for the GSM 1800rx. The behavior of the signal detector was linear for all operating frequencies. The deviation to the reference curve is between 0.7 and 1.6 dB. For the axial isotropy a difference of 1.9 dB was observed.

DECT

The DECT service was evaluated in ‘traffic-mode’ and ‘idle-mode’. For the ‘traffic-mode’ the signal generation the SMIQ06B was used. Unfortunately, the signal generator can only allocate 12 of 24 time slots. Hence evaluation was limited to a maximum of 12 time slots in the 'traffic-mode'. Table 3-2 summarizes the results for different configurations for the traffic mode. The detector shows a linear characteristic for different configurations. Beside that, it can be seen that the system overestimates the actual signal strength.

Depending on the number of occupied time slots the deviation to the reference curve varies between 5 and 12 dB. Changing the orientation from vertical to horizontal leads to a change of the measurement results by -2.3 dB. A change of the slot configuration, while keeping the total number of occupied slots constant, has only a negligible influence on the results.

For the ‘idle-mode’ a commercially available DECT system from AEG was used. The measurement range was adapted to field values one encounters in real world scenarios. Figure 3-4 shows the performance of the EME SPY 120. The results highlight a level dependent variation. For electric field values smaller than 103 dBμV/m, the exposimeter overestimates, while for higher values the DUT underestimates the electromagnetic field.

UMTS uplink

Table 3-2 gives the results for the UMTStx band. The characteristic of the detector was linear but depends on the operating frequency. An offset between -2.8 dB and +3.6 dB from the reference curve could be seen. The difference between a vertical and horizontal orientation of the exposimeter was around 2 dB.

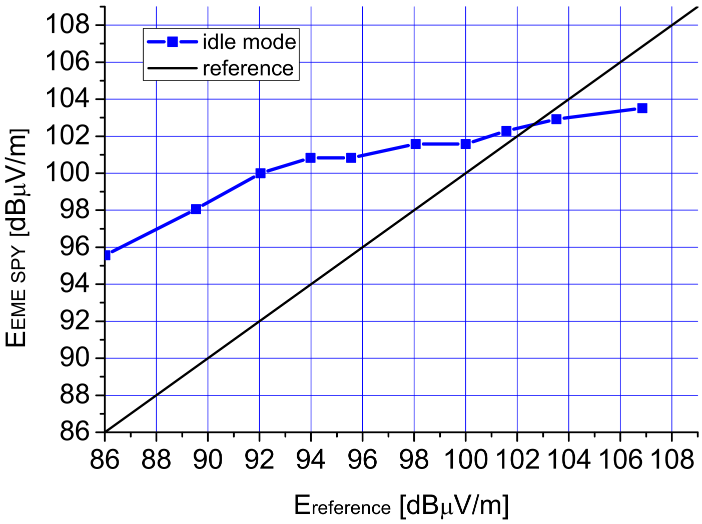

Figure 3-4: Comparison of measured electromagnetic fields in the DECT band (idle mode) with EME SPY 120 and a RMS reference system.

UMTS downlink

Table 3-2 summarizes the results for the UMTS downlink. The detector showed a linear characteristic but the results depend on the operating frequency. However, the offset deviation is smaller than for the UMTS uplink and varies between -0.3 dB and +1.6 dB with respect to the reference curve. The difference between a vertical and horizontal orientation of the exposimeter was smaller than 0.5 dB.

ISM-band

The service that is mainly using the ISM band at 2.4 GHz is wireless LAN communication. One of the most common used standards in the 2.4 GHz band is the IEEE 802.11g. It allows a maximum throughput of 54 MBit/s. It uses different modulation schemes like orthogonal frequency division multiplexing (OFDM) or complementary code keying (CCK), which depends on the instantaneous data rate of the WLAN link, see (Bing, 2007). In order to guarantee that the modulation does not change during the evaluation and in order to receive reproducible results, dummy data with the maximum data rate of 54 MBit/s (OFDM-Mode) was transmitted. The operating frequencies of the WLAN link were chosen to 2412 MHz (channel 1), 2437 MHz (channel 6) and 2472 MHz (channel 13). Table 3-2 summarizes the results. The characteristic of the detector showed a linear tendency, but with small variations. The non-linearity is caused by variations of the data rate during measurements, which could not be controlled perfectly. The variation of the measurement results compared to the reference is frequency dependent and varies between -0.7 dB and -5.3 dB. The axial isotropy for vertical and horizontal orientation of the exposimeter is 2 dB.

Cross-talk

The channel selection of the exposimeter is realized by bandpass filters, see (Mann et al., 2005). Due to the fact that the frequency separation between some service bands is very small, high order selective filters are required in order to neglect cross-talking. However, cross-talk effects were observed between various services with a maximum out of band reading of 0.56 V/m. Table 3-3 summarizes the affected bands:

Table 3-3: Affected services of cross-talk effects.

Active service	Affected service
UMTSrx	DECT
TETRA	TV 4-5
TV 4-5	GSM 900tx
GSM 1800tx	GSM 1800rx
GSM 1800tx	DECT
GSM 1800rx	DECT
GSM 1800rx	UMTStx
DECT	UMTStx
UMTStx	DECT
UMTStx	UMTSrx

Further evaluations showed that the system do not resolve this problem on a software basis. If the signal in an affected service band featured a value smaller than the cross-talk level then this signal could not be detected. This shows that the exposimeter provides incorrect results due to cross-talking, and results must be examined conditionally.

Response to multiple signals

In real world scenarios multiple signals occur in the same band. Therefore, the response to multiple signals of the DUT has to be investigated.

Therefore, two identical signal generators from R&S were used. The output of the two signal sources were combined with a combiner, amplified and then transmitted. Figure 3-5 shows the results for two signals operating in the GSM 1800tx band for different slot configurations. The carrier frequency of signal 1 was 1752 MHz and signal 2 1750 MHz. The according transmission powers were 4 dBm and 0 dBm. The first digit in the slot configuration gives the total number of occupied time slots for signal 1 and the second digit for signal 2 respectively. The results show that the reading of the DUT is constant when at least one time slot of signal 1 is occupied. This shows that the system only detects the stronger service.

Figure 3-6 shows the results for two signals operating in the GSM 1800rx band for different slot configurations. The carrier frequency of signal 1 was 1842 MHz and signal 2 1840 MHz. The according transmission powers were 0 dBm and 4 dBm. The first digit in the slot configuration gives the total number of occupied time slots for signal 1 and the second digit for signal 2 respectively. According to the GSM 1800rx results there must be at least one signal that features eight occupied time slots to get a reading in the downlink band. Hence we allocated signal 1 eight time slots. The results show that the reading of the DUT is constant as long as signal 2 features less than eight occupied time slots. Only when signal 2 also occupies 8 time slots the reading of the exposimeter changes. This shows again that only a signal with a full slot configuration is detected. This can easily lead to an underestimation of the field strength, e.g. see slot configuration (4-8). Further evaluations with two signals, having eight occupied time slots, where $P_{t1}=P_{t2}$ showed that only one signal is detected by the exposimeter.

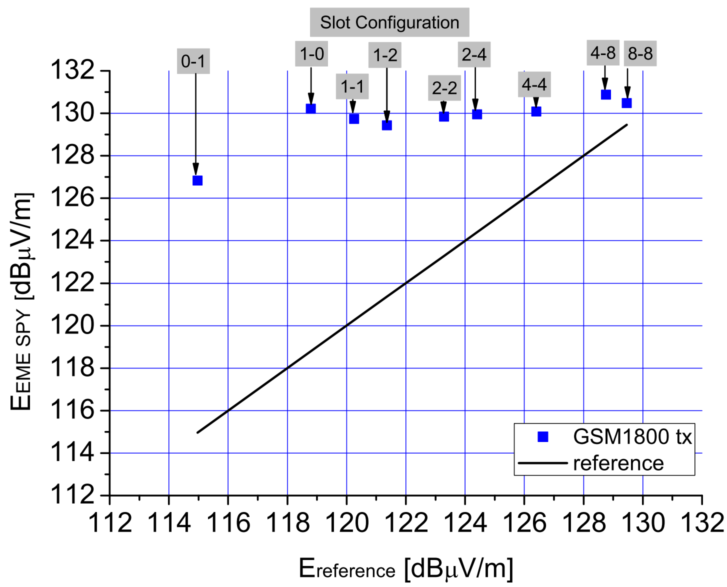

Figure 3-5: Comparison of measured electromagnetic fields in the GSM 1800tx band with EME SPY 120 and a RMS reference system for two input signals. The digits in the slot configuration indicate the number of occupied time slots for signal 1 (P_{t1} = 4 dBm) and signal 2 (P_{t2} = 0 dBm).

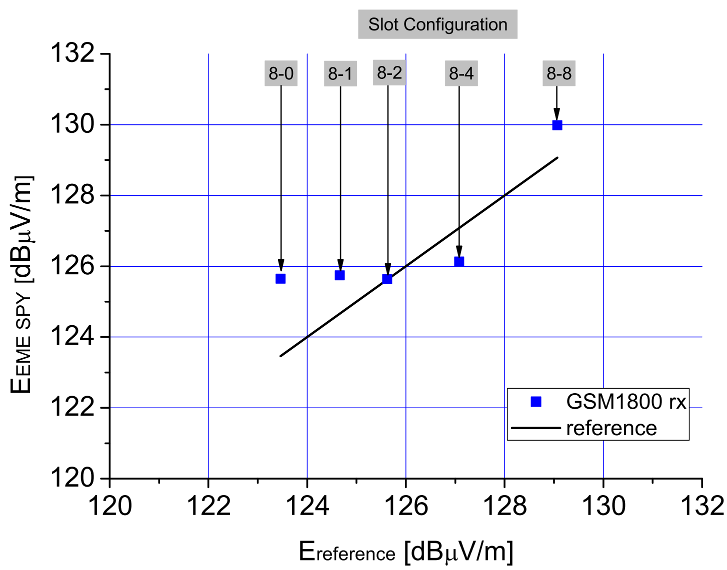

Figure 3-6: Comparison of measured electromagnetic fields in the GSM 1800rx band with EME SPY 120 and a RMS reference system for two input signals. The digits in the slot configuration indicate the number of occupied time slots for signal 1 (Pt1 = 0 dBm) and signal 2 (Pt2 = 4 dBm).

Device-dependent variability

Due to the parallel employment of different EME SPY 120 devices in experimental and epidemiological studies, like in (Berg et al., 2006), it is important to evaluate the device dependent variability. Therefore, the accuracy of a second EME SPY 120 device is analyzed, indicated with a ‘B’. The analysis follows the same procedure as described in the Chapter Material and Methods. The results are summarized in Table 3-4.

Comparing the results of Table 3-2 and Table 3-4, a different characteristic of the two measurement devices can be observed. For device A, e(900 MHz) calculates to 0.85 dB, whereas for device B has a deviation of e(900 MHz)=3.4 dB. Furthermore device 'A' shows the smallest field values for the carrier frequency of 880 MHz and device 'B' for 915 MHz. One of the maximum differences in the measurement results between device A and B occurs in the TV band at 830 MHz. Here device 'A' underestimates the field values by -14.5 dB and device 'B' by -8 dB. The total difference between these two values is 6.5 dB. This fact makes it necessary to calibrate each measurement device separately.

Furthermore it is highly recommended to calibrate the system before and after the measurement campaign in order to track system dependent variances which might have an impact on the calibration files.

Discussion

Impact on epidemiology

In this study substantial measurement uncertainties were observed for numerous specific slot or frequency configurations. This raises several implications for the use of exposimeters for epidemiological exposure assessment. In epidemiology one is interested in differentiating between highly and lowly exposed groups or in the exposure ranking within a study collective. Exposimeters allow collecting thousands of measurements for each individual in order to calculate average exposure, which is mainly of interest in epidemiology. Therefore, over and underestimation of the RF-EMF for specific slot or frequency configurations, as observed in this study, will

Table 3-4: Average deviation e(f) of the measured electric field of device B to the reference measurement for a vertical orientation of the DUT.

Tetra	380 MHz	390 MHz	400 MHz
B - 4 Slots	5.87 dB	6.3 dB	4.62 dB
B - 3 Slots	3.61 dB	5.28 dB	4.52 dB
B - 2 Slots	5.21 dB	6.88 dB	6.27 dB
B - 1 Slot	10.97 dB	12.5 dB	11.96 dB
TV 4-5	470 MHz	650 MHz	830 MHz
B	-3 dB	-3.7 dB	-8 dB
GSM 900tx	880 MHz	900 MHz	915 MHz
B - 8 Slots	1.98 dB	3.4 dB	0.72 dB
B - 4 Slots	4.8 dB	6.11 dB	3.49 dB
B - 2 Slots	7.61 dB	8.99 dB	6.33 dB
B - 1 Slot	10.31 dB	11.39 dB	9.07 dB
GSM 900rx	925 MHz	940 MHz	960 MHz
B	-2.66 dB	0.99 dB	-1.62 dB
GSM 1800tx	1710 MHz	1750 MHz	1780 MHz
B - 8 Slots	4.41 dB	4.61 dB	2.4 dB
B - 4 Slots	7.39 dB	7.75 dB	5.78 dB
B - 2 Slots	10.13 dB	10.29 dB	8.59 dB
B - 1 Slot	12.12 dB	12.06 dB	10.85 dB
GSM 1800rx	1800 MHz	1840 MHz	1880 MHz
B	1.68 dB	0.83 dB	-1.53 dB
DECT	-	1890 MHz	-
B - 12 Slots		7.59 dB	
B - 4 Slots		11.07 dB	
B - 2 Slots		12.26 dB	
B - 1 Slot		12.54 dB	
UMTStx	1920 MHz	1950 MHz	1980 MHz
B	1.39 dB	3.1 dB	2.17 dB
UMTSrx	2110 MHz	2140 MHz	2170 MHz
B	0.91 dB	0.79 dB	-1.05 dB
WLAN	2412 MHz	2437 MHz	2472 MHz
B	1.68 dB	0.74 dB	-0.73 dB

equal each other to some extent and produce much smaller error on the total average exposure. This principle could be demonstrated with sensitivity analyses in the QUALIFEX study, see (Frei et al., 2009b)

Systematic errors are of major concern in epidemiology. Systematic errors could arise from varying measurement accuracy between devices as observed in this study. In practice, this effect does not seem to be crucial. In QUALIFEX, 8 different devices were used to measure personal exposure but including them as predictors in the final exposure prediction model (Frei et al., 2009b) did not change the model coefficients much. Moreover, none of the devices was a significant exposure predictor, and the explained variance of the exposure prediction model increased only by 52 % to 53 %. In this study we found that DECT and GSM uplink bands are considerably overestimated by the exposimeter if only a few slots are occupied. This situation occurs when the study participant or a person nearby is using a phone. On the other hand, GSM base station emissions are only detected if all 8 slots are occupied, which is a problem for measuring traffic channels. This suggests that exposimeter measurements overestimate GSM uplink exposure whereas GSM downlink is underestimated. Applying correction factors to correct for this would be appealing. However, correction factors vary considerably according to the assumption about frequency and slot configuration, and they are only appropriate if they reflect the typical situation in the study area. In conclusion, measurement accuracy is a major challenge for personal exposure measurements and should further be scrutinized. Over- and underestimation of specific configurations yields to considerably smaller overall errors in the exposure assessment. Nevertheless, further investigation of the measurement accuracy would allow for obtaining correction factors for different situations and services and improve the assessment of the personal exposure more accurately.

Conclusion

A novel calibration measurement setup for PEMs was built and the measurement accuracy and the limits of the EME SPY 120 were evaluated in an anechoic chamber and measurement results were compared to a root mean square reference system. Different types of measurements were carried out for different services including TETRA, TV 4-5, GSM 900, GSM 1800, DECT, UMTS and communication in the

ISM band at 2.4 GHz. The results are summarized in tables, where the deviation of the recorded electric field of the exposimeter is compared to the reference electric field. Modulated signals representing the different services as real signals generated by appropriate testers were used.

The measurement results of the PEMs showed a good linear behavior of the signal detectors at all operating frequencies, except for DECT operating in the idle mode. The deviation of the recorded electric field levels from the exposimeter to the reference signal depends on the operating frequency and the slot configuration for TDMA based services. A deviation between -0.31 dB and +13 dB could be observed. Here the results indicate that peak detectors are used. For non-TDMA based services, the results showed mainly a frequency dependent behavior. The maximum deviation occurred in the TV band, which was between -8.32 dB and +1.6 dB. For WLAN signals (802.11g) the data rate also has an impact on the measurement results. This is due to the fact that different modulation methods are used for different data rates.

The deviation of the isotropy was between -2.3 dB and 5 dB for the horizontal and vertical orientations of the device.

Measurements with multiple signals in the same GSM 1800 band indicate that the system does not reliably detect multiple signals. This can lead to an underestimation of electric field values for measurement scenarios, where more than one signal is active at the same time.

Due to the signal dependent variations of the measurement results, reliable calibration factors can only be derived if network configurations are available of the measurement location. Therefore, potential proxies for specific network configurations and data traffic have to be evaluated. Further investigation of the measurement accuracy would allow for obtaining correction factors for different situations and services and therefore to improve the assessment of the personal exposure more accurately. In order to reduce the potential impact of systematic errors on the exposure classification, every single device should be calibrated separately.

When the biological relevance would be dominated by peak values, the EME SPY 120 would be an appropriate measurement device for such measurements.

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4 RF-EMF exposure distribution in a population sample

Article 3: Temporal and spatial variability of personal exposure to radio frequency electromagnetic fields

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Temporal and spatial variability of personal exposure to radio frequency electromagnetic fields ☆

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DECT cordless phone
Radio and television broadcast

A B S T R A C T

Background: Little is known about the population's exposure to radio frequency electromagnetic fields (RF-EMF) in industrialized countries.
Objectives: To examine levels of exposure and the importance of different RF-EMF sources and settings in a sample of volunteers living in a Swiss city.
Methods: RF-EMF exposure of 166 volunteers from Basel, Switzerland, was measured with personal exposure meters (exposimeters). Participants carried an exposimeter for 1 week (two separate weeks in 32 participants) and completed an activity diary. Mean values were calculated using the robust regression on order statistics (ROS) method.
Results: Mean weekly exposure to all RF-EMF sources was 0.13 mW/m^2 (0.22 V/m) (range of individual means 0.014–0.881 mW/m^2). Exposure was mainly due to mobile phone base stations (32.0%), mobile phone handsets (29.1%) and digital enhanced cordless telecommunications (DECT) phones (22.7%). Persons owning a DECT phone (total mean 0.15 mW/m^2) or mobile phone (0.14 mW/m^2) were exposed more than those not owning a DECT or mobile phone (0.10 mW/m^2). Mean values were highest in trains (1.16 mW/m^2), airports (0.74 mW/m^2) and tramways or buses (0.36 mW/m^2), and higher during daytime (0.16 mW/m^2) than nighttime (0.08 mW/m^2). The Spearman correlation coefficient between mean exposure in the first and second week was 0.61.
Conclusions: Exposure to RF-EMF varied considerably between persons and locations but was fairly consistent within persons. Mobile phone handsets, mobile phone base stations and cordless phones were important sources of exposure in urban Switzerland.

1. Introduction

There has been a substantial increase of exposure to radio frequency electromagnetic fields (RF-EMF) over the past 20 years due to the introduction of new technologies, especially technology related to mobile communication (Neubauer et al., 2007). In recent years, this development has led to concerns regarding possible effects of RF-EMF on health-related quality of life and other health outcomes (Schreier et al., 2006).

In principle, two different types of RF-EMF exposure sources can be distinguished: sources which are applied close to the body usually causing high and periodic short-term exposures mainly to the head (e.g. mobile phones) and environmental sources which, in general, cause lower but relatively continuous whole-body exposures (e.g. mobile phone base stations). While exposure from mobile phones can be assessed using self-reported mobile phone use or operator data (Vrijheid et al., 2008), valid assessment of exposure to environmental fields is more challenging. Current methods have several limitations. For example, studies examining the association between symptoms and radiation from mobile

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phone base stations generally assessed exposure using the lateral distance of the residence to the next base station (Navarro et al., 2003; Santini et al., 2003), which has been shown to be inadequate (Bornkessel et al., 2007; Neitzke et al., 2007; Neubauer et al., 2007; Schüz and Mann, 2000). Other studies used spot measurements, mostly in bedrooms, as a proxy for habitual exposure (Hutter et al., 2006; Navarro et al., 2003; Preece et al., 2007). However, it is unknown how representative such measurements are for the average exposure in a room (Bornkessel et al., 2007) and whether they reflect long-term exposure in a person (Neubauer et al., 2007). Furthermore, previous research generally considered one source of RF-EMF only.

Newly developed exposure meters (exposimeters) are useful to measure personal exposure to environmental RF-EMF in everyday life and have been recently recommended (Ahlbom et al., 2008; Neubauer et al., 2007). The use of exposimeters leads to a better understanding of exposure variability within the population, the contribution of different sources to total exposure and the spatial and temporal variability of exposure during daily life activities. In addition, the reproducibility of personal exposure to environmental RF-EMF can be examined, which is an important prerequisite to conduct epidemiological studies (Ahlbom et al., 2004). In the present study, we investigated the levels, the sources and the variability of exposure to environmental RF-EMF in a group of adult volunteers living in a Swiss city using personal exposimeters.

2. Materials and methods

We collected personal weekly RF-EMF measurements and corresponding diary data from 166 study participants. This study is part of a wider project known as the QUALIFEX study (health-related quality of life and radio frequency electromagnetic field exposure: prospective cohort study; see www.qualifex.ch).

2.1. Study participants

Participants were selected from the city of Basel (Switzerland) and surroundings. Eligibility criteria were age 18 years or above and residency in the study area. Between April 2007 and February 2008, we recruited six study participants each week. In order to maximize the range of exposure levels, four different recruitment strategies were chosen: firstly, we recruited 17 individuals from a list of addresses close to mobile phone base stations, where measurements had previously been performed to ensure compliance with the standard limits for mobile phone base stations. Secondly, we used a propagation model for RF-EMF in the study area (Bürgi et al., 2008) to identify ten study participants living in areas highly exposed to mobile phone base stations and eight participants living in areas highly exposed to broadcast transmitters. Thirdly, we recruited two persons working exclusively outdoors. The remaining 129 volunteers registered for participation on our homepage or by telephone (self-selected volunteers). We repeated the measurements in a sub-sample of the study population (32 participants) during a second week (repeatability study).

2.2. Personal measurements

We used seven personal exposure meters (exposimeters) EME Spy 120 (SATIMO, Courtaboeuf, France, http://www.satimo.fr/). One of them was used as replacement device. The EME Spy 120 is a portable measurement device (weight 450 g) which detects power flux density between 0.0067 and 66.3 mW/m^2 (electrical field strength between 0.05 and 5 V/m) over time. It measures 12 different bands of RF-EMF ranging from radio FM (frequency modulation; 88–108 MHz) to W-LAN (wireless local area network) (2.4–2.5 GHz). The measured frequency bands and further characteristics of the EME Spy 120 are summarized in Table 1.

A study assistant visited participants at home and handed over the exposimeter device, a personal diary and a questionnaire covering exposure relevant behavior. The exposimeter was programmed to take measurements every 90 s during 1 week. Participants were asked to document all locations at which they stayed for at least 10 min in the diary. We distinguished between locations in the house (bedroom; living room/kitchen/bathroom; study and other rooms), at the workplace, at other places (e.g. friends place, sports hall, shopping) and traveling (by tramway, bus, car or train). The study participants were advised to complete the diary continuously. In addition, they were asked to record all calls they made or received using a mobile or digital enhanced cordless telecommunications (DECT) phone. Participants were instructed to carry the exposimeter at the belt or in a backpack when moving. When stationary (e.g. in the bedroom or in the office), they were asked to place the exposimeter in the vicinity but not exactly at the same place during the whole week. They were asked not to place the exposimeter on the floor or in the close vicinity (less than 30 cm) of a wall or of an electrical device. After 1 week, the study assistant collected the exposimeters, diaries and exposure questionnaires.

2.3. Calculation of mean values

For each individual we calculated a weekly arithmetic mean value for each frequency band. To allow for measurements below the detection limit of 0.0067 mW/m^2, arithmetic mean values were calculated using the robust regression on order statistics (ROS) method (Helsel, 2005). The weekly means for each frequency band were derived by calculating mean values for daytime on workdays, nighttime on workdays and for weekends for each participant separately, followed by the calculation of appropriately weighted weekly means. We obtained total weekly RF-EMF exposure for each individual by adding up the mean value for each frequency band. RF-EMF exposure at each location was

Table 1
Measured frequency bands and characteristics of the EME SPY 120 exposimeter.

Band	Abbr.	Frequency (MHz)	Description
FM	FM	88–108	FM radio broadcast transmitter
TV3	TV	174–223	TV broadcast transmitter
Tetrapol	Tetrapol	380–400	Mobile communication system for closed groups
TV4/5	TV	470–830	TV broadcast transmitter
GSM900 uplink	Uplink	880–915	Transmission from handset to base station
GSM900 downlink	Downlink	925–960	Transmission from base station to handset
GSM1800 uplink	Uplink	1710–1785	Transmission from handset to base station
GSM1800 downlink	Downlink	1805–1880	Transmission from base station to handset
DECT	DECT	1880–1900	Digital enhanced cordless telecommunications
UMTS uplink	Uplink	1920–1980	Transmission from handset to base station
UMTS downlink	Downlink	2110–2170	Transmission from base station to handset
W-LAN	W-LAN	2400–2500	Wireless local area network
Total			Sum of all bands
Other characteristics			
Measurement range	0.0067–66.3 mW/m^2 (0.05–5 V/m)		
Measurement cycle	4–255 s		
No. of samples stored	7168		
Size ($L \times W \times H$)	$195 \times 95.4 \times 75$ mm		
Weight	450 g		

GSM (global system for mobile communication) and UMTS (universal mobile telecommunications system) refer to mobile communication technology standards.

calculated from all available measurements for the respective location. Measurements that were taken when study participants used their mobile or DECT phones were considered separately and excluded from the calculation of mean values. Therefore, the calculated mean values represent exposure from environmental sources other than the own phone use. The second measurements of participants that took part in the study twice were only used for evaluation of repeatability of exposure assessments.

Statistical analyses were carried out using STATA version 9.2 (StataCorp, College Station, TX, USA) and R version 2.7.1. All calculations were done with the values for the power flux density (mW/m^2). We calculated Spearman rank correlations to examine the repeatability of the measurements and to assess correlations between total exposure and exposure at different locations and times.

2.4. Data cleaning

We occasionally observed coupling (out of band responses) between GSM 1800 downlink and the DECT phone frequency band. We therefore censored DECT measurements taken outdoors, in trains, trams, buses and cars showing a value above 0.027 mW/m^2 (0.1 V/m). Our replacement exposimeter, which was used for five study participants, did not correctly measure W-LAN and universal mobile telecommunications system (UMTS) downlink. In order to obtain the total RF-EMF exposure of these individuals, exposure to W-LAN and UMTS downlink was imputed using the mean of all study participants for the two frequency bands. For the imputation of the W-LAN values, we stratified according to whether participants owned W-LAN at home or not. Finally, we observed that occasionally three of our exposimeters measured continuously implausible small values (between 0.0067 and 0.0265 mW/m^2) of FM radio broadcasting, GSM 1800 uplink, UMTS up- and downlink and W-LAN. For FM, three participants were affected, for GSM 1800 one participant, for UMTS uplink two and for downlink nine participants and for W-LAN 25 participants. For these participants we reset the detection limit for the respective frequency bands above the erroneous measurements in the robust ROS calculations.

2.5. Quality control and sensitivity analysis

To evaluate the quality of our data we performed three sensitivity analyses. Firstly, we occasionally observed inconsistencies between the diary entries and exposimeter measurements, mainly because of time shifts. These inconsistencies were corrected by adjusting the diary data based on the measurement pattern. In sensitivity analysis 1, we calculated the mean values by omitting these adjusted data. Secondly, there are uncertainties concerning the measuring accuracy of the exposimeter in the different frequency bands. Alternative frequency-specific calibration factors were provided by the Dutch Radio Communications Agency and the National Institute for Public Health and the Environment of the Netherlands (RIVM), which independently evaluated the calibration factors provided by SATIMO in a gigahertz transverse electromagnetic (GTEM) cell (Bolte et al., 2008) with an EME Spy 121. These calibration factors were determined as follows: Vertically polarised fields were applied to the front of the EME Spy unit: a pulsed field for TDMA (Time Division Multiple Access) bands (Tetrapol (Terrestrial Trunked Radio Police), GSM (Global system for mobile communication) 900 uplink, GSM 1800 uplink, DECT), continuous wave for the other bands. In sensitivity analysis 2, the measurements were multiplied with these alternative calibration factors before calculating the mean values. Thirdly, the measurement accuracy of the exposimeters might be temporally instable. The Federal Office of Metrology performed calibrations in March, June and November 2007 as well as in February 2008 using continuous wave signals to determine changes in the measurement sensitivity. For each exposimeter and frequency band, the temporal calibration factors were determined for the corresponding time period. In sensitivity analysis 3, we multiplied the measurements with the corresponding temporal calibration factors in order to obtain the mean values.

3. Results

3.1. Characteristics of study participants

The characteristics of the study participants are shown in Table 2. Mean age was 42.6 years (range: 18–78 years) and 92 (55.4%) participants were women. In total, 202 weekly exposimeter measurements were taken between April 2007 and February 2008. Four measurements had to be excluded because the exposimeter did not record any data (one case) or the diary was poorly filled in (three cases). The level of educational attainment was high: two-thirds of participants had university degrees.

Table 2
Characteristics of the study participants.

	N	%
Sex		
Male	74	44.6
Female	92	55.4
Age (years)		
18–34	62	37.4
35–49	50	30.1
50–64	41	24.7
>64	13	7.8
Education (highest level)		
Compulsory schooling or less	2	1.2
Vocational training	35	21.3
In higher education (high school)	18	11.0
Higher education/University	109	66.5
Recruitment strategy		
Proximity to mobile phone base station	27	16.3
Proximity to broadcast transmitter	8	4.8
Working outdoors	2	1.2
Self-selected volunteers	129	77.7
Ownership of wireless devices		
Persons owning a mobile phone handset	146	88.0
Persons owning a cordless phone	128	77.1
Persons owning W-LAN	55	33.1

Thirty-two volunteers participated in the repeatability study. We excluded one participant who moved house and one participant who placed the exposimeter closer than 30 cm to a DECT cordless phone over night in the second week. The two weekly measurements were on average 20.7 weeks (range 3–41 weeks) apart.

3.2. Mean exposure and contributions of different RF-EMF sources

The mean exposure to all measured RF-EMF sources over the whole week was 0.13 mW/m^2 (0.22 V/m). As shown in Fig. 1, exposure was mainly caused by mobile phone base stations (downlink; 32.0%), mobile phone handsets (uplink; 29.1%) and DECT cordless phones (22.7%). Within the uplink frequency, GSM 900 contributed 66.5%, GSM 1800 32.8% and UMTS 0.7% of exposure. Within the downlink frequency, GSM 900 contributed 28.7%, GSM 1800 64.6% and UMTS 6.7%. Mean exposure among the 27 persons who were invited because they lived close to a mobile phone base station was 0.21 mW/m^2 (68.1% from base stations). It was 0.24 mW/m^2 (48.9% from broadcast transmitters) for the eight participants who were invited because they lived in the proximity of a broadcast transmitter and 0.11 mW/m^2 in the remaining participants (Fig. 2). In the latter group of self-selected volunteers, the main contributions were uplink (38.1%), cordless phone (24.3%) and mobile phone base station (21.8%). Mean total exposure of persons owning a mobile phone handset was higher (0.14 mW/m^2) than for persons not owning a mobile phone handset (0.10 mW/m^2), mainly due to the higher contribution of mobile phone handset radiation (30.0% and 19.6%, respectively). In the subgroup of persons owning a DECT phone, mean total exposure was higher (0.15 mW/m^2) compared to those not owning a DECT phone (0.10 mW/m^2). The contribution of DECT radiation was 26.2% for persons owning a DECT phone and 9.1% for persons not owning a DECT phone. Persons owning W-LAN had a higher contribution of W-LAN radiation to total exposure (7.7%) than those not having W-LAN (2.3%), but the mean total exposure was only slightly elevated.

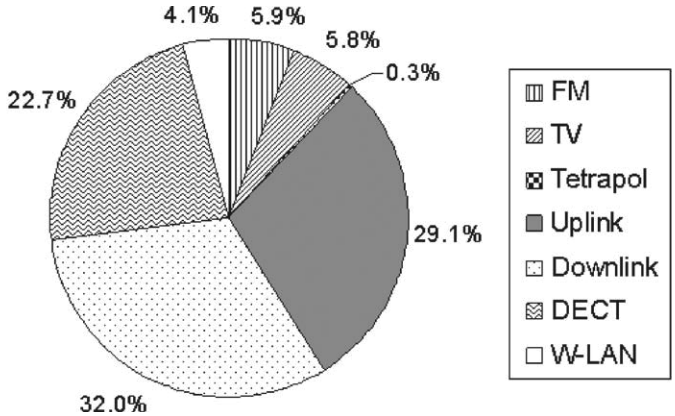

Fig. 1. Mean contributions of the RF-EMF sources to total exposure (power flux density) (for description of the abbreviations in the figure see Table 1).

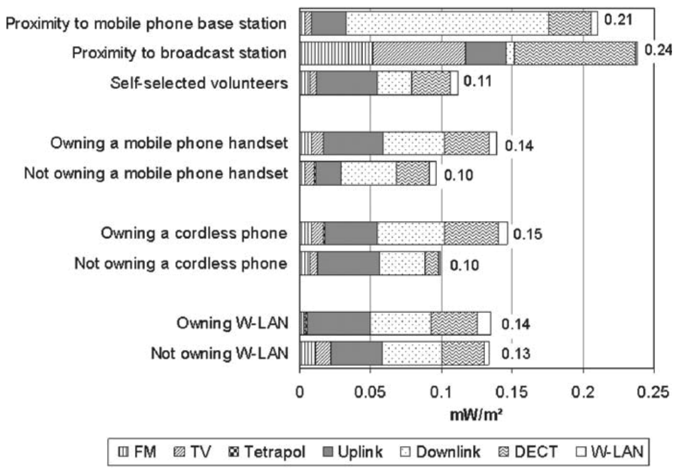

Fig. 2. Mean RF-EMF exposure (power flux density) of different sources in different subgroups of the study participants (for description of the abbreviations in the figure see Table 1).

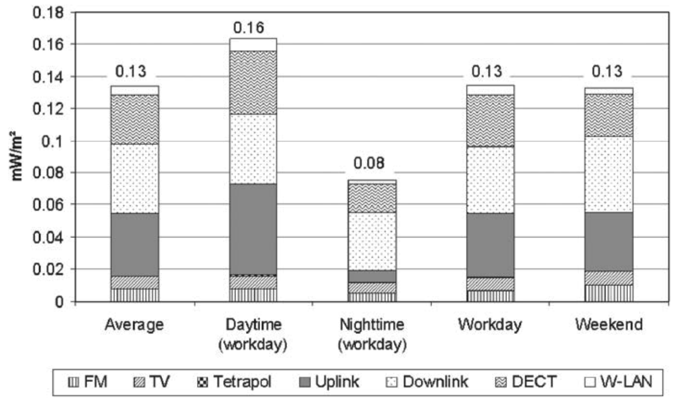

Fig. 3. Mean RF-EMF exposure (power flux density) of different sources at different times (for description of the abbreviations in the figure see Table 1).

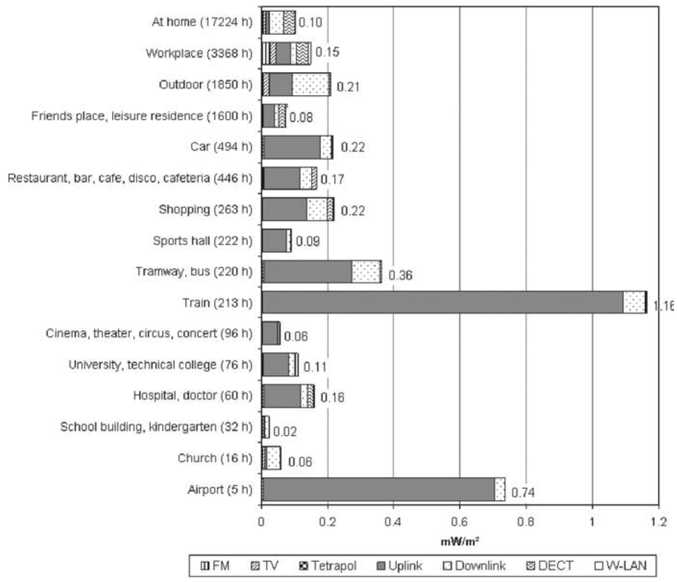

Fig. 4. Mean RF-EMF exposure (power flux density) at different locations and for different frequency bands. The hours indicate the total time of all study participants spent at each location (for description of the abbreviations in the figure see Table 1).

3.3. Mean exposure at different times and locations

Exposure on workdays was higher during daytime (6 am–22 pm) than nighttime (means 0.16 and 0.08 mW/m^2, respectively) (Fig. 3). During daytime exposure was mainly due to mobile phone handsets (34.2%) and mobile phone base stations (26.9%), whereas at night it was mainly due to mobile phone base stations (47.2%) and DECT phones (22.9%). Exposure levels and contributions of different sources at workdays and weekends were virtually the same (mean 0.13 mW/m^2).

Fig. 4 details mean values measured at different locations. The highest mean values were recorded for train journeys, stays at the airport and rides on the tramway or bus. The smallest exposures were measured in school buildings and kindergartens, churches and in cinemas, theatres, the circus and during concerts. In all locations, mobile telecommunication (up- and downlink) was the main source of exposure. Mobile phone base stations were the most important contributor in churches (70.2%), in school buildings and kindergartens (56.0%), outdoor (52.6%) and at home (42.6%). In all other categories, exposure was mainly due to mobile phone handsets (airport 95.2%; train 93.5%; cinema, etc., 82.8%; sports hall 79.1%; car 78.5%; tramway, bus 73.5%; hospital, doctor 69.0%; university, technical college 68.3%; restaurant, etc., 65.1%; shopping 60.2%; friends place, leisure residence 43.6%; workplace 29.0%). With respect to exposure in public transport we found that mobile phone handset exposure was higher for persons owning a mobile phone handset compared those not (1.11 vs. 0.87 mW/m^2 in trains and 0.27 vs. 0.23 mW/m^2 in tramways and buses). Contributions from DECT were relevant at home (32.6%), at the workplace (24.1%) and at the place of friends (25.6%). The contributions of FM radio and television (TV) broadcast transmitters were relatively small in all categories. Mobile phone uplink measurements during a call with a mobile phone were on average 4.87 mW/m^2 and DECT measurements during a cordless phone call 2.98 mW/m^2.

Spearman correlations between total exposure and components of total exposure were 0.95 (95%-CI: 0.93–0.96) with exposure during workdays, 0.68 (0.59–0.75) with weekend exposure, 0.73 (0.65–0.80) with exposure at home, 0.53 (0.41–0.63) with exposure in the bedroom, 0.91 (0.88–0.94) with exposure during daytime and 0.67 (0.57–0.74) with exposure during nighttime.

3.4. Exposure contrasts between individuals

In Table 3 more details about exposure distributions is given. We compared mean exposure levels at different places and times between individuals. The lowest weekly average was 0.014 mW/m^2 and the highest 0.881 mW/m^2, resulting in an exposure contrast factor of 61 (maximum weekly value divided by minimum weekly value). The exposure range at the workplace (exposure contrast factor 772) was higher than at home (295). Similarly, a higher exposure contrast could be seen at nighttime (factor 429) compared to daytime (factor 76) and on weekends (factor 186) compared to workdays (factor 61).

3.5. Repeatability of exposimeter measurements

The results of the repeatability study yielded a Spearman correlation coefficient of 0.61 (95%-CI: 0.32–0.79) comparing mean total exposure of the first and second week of 30 study participants. The mean difference between the first and the second week mean value was 0.02 mW/m^2 with a standard deviation of 0.12 mW/m^2. We also compared exposure of the first and second week at home and in the bedroom and obtained Spearman correlation coefficients of 0.74 (95%-CI: 0.52–0.87) and 0.81 (95%-CI: 0.63–0.91), respectively.

3.6. Sensitivity analyses

As shown in Table 4, results from sensitivity analysis 1, which used the unadjusted diary data, were virtually the same as those from the main analysis based on adjusted data. This was true for total exposure (deviation from the original mean 0.5%) and for all frequency bands. In sensitivity analysis 2 (use of frequency-specific calibration factors), total RF-EMF was 0.16 mW/m^2 (deviation from the original mean 18.9%). The contributions of the frequency bands were very similar compared to the original data. When using calibration factors accounting for the temporal shifts of the exposimeters (sensitivity analysis 3), total exposure was 0.12 mW/m^2 (deviation from the original mean 14.1%). Again, the proportion of the contributions of all frequency bands was similar.

4. Discussion

This study quantified mean exposure levels to RF-EMF across individuals and locations and determined the contributions from different sources to total exposure during activities of daily living for volunteers living in Basel, Switzerland. We found that the mean exposure to all RF-EMF sources combined over 1 week was 0.13 mW/m^2 (0.22 V/m). Major sources included mobile phone base stations, mobile phone handsets and DECT cordless phones, and exposure levels were highest when traveling in trains, tramways and buses.

4.1. Strengths and weaknesses

To our knowledge, this is the first study to assess RF-EMF exposure by combining personal measurements with diary data, and it shows that this approach is feasible. The use of diaries allowed us to relate measurements to different locations, to examine the contributions of a range of sources and to investigate temporal variation in exposure. We put a lot of effort to ensure data quality and the results of our extensive sensitivity analyses indicate that our main results are robust.

We used personal exposimeters, an approach widely recommended for the study of population exposure to RF-EMF (Ahlbom et al., 2008; Neubauer et al., 2007). Unlike stationary devices, exposimeters move with study participants and record exposure not only at the place of living, but also at the workplace, when traveling, and during other activities of daily living. Exposimeters provide objective measurements and avoid recall bias, a common problem in case–control studies that rely on participants' reports of past phone use (Vrijheid et al., 2008). In addition, we were able to measure several RF-EMF sources separately. This allowed us to identify the most relevant exposure sources.

We chose to calculate mean values using the robust regression on order statistics method because a substantial proportion of personal exposimeter measurements in everyday life is below the detection limit (Knafl et al., 2008; Thuróczy et al., 2008). Robust ROS is a method to calculate summary statistics for left censored data by fitting an assumed distribution for the values below the detection limit (a full description of the method can be

Table 3
Distribution of total average individual exposure at different places and times in our study population.

	Mean (mW/m^2)	Minimum (mW/m^2)	5% quantile (mW/m^2)	25% quantile (mW/m^2)	Median (mW/m^2)	75% quantile (mW/m^2)	95% quantile (mW/m^2)	Maximum (mW/m^2)	Exposure contrast (Max/Min)
Average	0.134	0.014	0.030	0.054	0.092	0.163	0.351	0.881	61
At home	0.100	0.004	0.008	0.023	0.044	0.105	0.334	1.212	295
Workplace	0.147	0.003	0.006	0.023	0.061	0.154	0.534	2.460	772
Daytime	0.164	0.014	0.034	0.070	0.127	0.209	0.445	1.063	76
Nighttime	0.076	0.003	0.005	0.014	0.028	0.086	0.245	1.367	429
Workday	0.134	0.013	0.027	0.055	0.096	0.170	0.353	0.776	61
Weekend	0.133	0.007	0.014	0.031	0.064	0.148	0.474	1.243	186

Table 4
Total weekly values and the contribution from different sources obtained with the three different sensitivity analyses (for abbreviations of the legend see Table 1).

	Relative change	Total (mW/m^2)	FM (%)	TV (%)	Tetrapol (%)	Uplink (%)	Downlink (%)	DECT (%)	W-LAN (%)
Original	–	0.13	5.9	5.8	0.3	29.1	32.0	22.7	4.1
Non-adjusted data (sensitivity analysis 1)	−0.5%	0.13	6.0	5.9	0.3	29.4	32.2	23.0	3.2
Frequency specific calibration factors (sensitivity analysis 2)	18.9%	0.16	3.4	3.6	0.2	29.8	35.6	25.5	2.0
Temporal calibration factors (sensitivity analysis 3)	−14.1%	0.12	5.7	5.6	0.2	28.1	34.3	22.3	3.8

found in Helsel, 2005). In our calculations we assumed a log-normal distribution, which was also used in other studies (Joseph et al., 2008). In an earlier analysis we found that summary statistics of exposimeter data with nondetects calculated by robust ROS are reliable (Röösli et al., 2008).

The interpretation of exposimeter measurements when placed in close proximity to the body is not straightforward. Measurements taken when the device is carried in a backpack or at the belt of the subjects are affected by changes in the field distribution induced by the presence of the human body (Knafl et al., 2008). Preliminary results of an ongoing study on the reliability of exposimeter reading in respect of real exposure indicate that exposimeters tend to underestimate true exposure by about a factor of two due to shielding effects of the body (Neubauer et al., 2008). Our study participants were advised to place the exposimeters in their vicinity when not moving. In this situation no or only weak shielding effects are expected. Outdoor exposure, on the other hand, may have been underestimated in our study, because the exposimeter was carried close to the body most of the time.

The assessment of exposure from handsets and other sources close to the body with personal exposimeters is limited: measurements taken during calls with mobile or DECT phones strongly depend on the distance between the emitting device and the exposimeter and do not reflect maximum exposure at the head of the person making the calls (Inyang et al., 2008). We therefore disregarded measurements when participants used their own mobile or cordless phones. Other persons' phones are generally distant enough from the device, resulting in valid measurements of the environmental whole-body RF-EMF exposure. Our estimates of environmental RF-EMF exposure thus include other people's mobile phone handsets, but not radiation from own use of such handsets (passive mobile phone exposure). For a comprehensive dosimetry of far and near field sources, exposimeters may not be sufficient and one may consider close to body sources separately. Of note, despite the fact that we omitted measurements taken when using their own mobile phone handset, persons owning a mobile phone were more exposed to mobile phone handset radiation. An explanation for this might be that mobile phone handsets contribute to exposure also when they are just switched on but not used (due to hand-overs), or that study participants forgot to note some of their mobile phone calls in the diary.

Due to the novelty of the exposimeter device, the data on its accuracy are still limited. The alternative frequency-specific calibration factors for our sensitivity analysis were independently determined by applying similar signals like the manufacturer did. These alternative calibration factors differed in the range from −25% up to 48% compared to the ones that we obtained from the manufacturer and this may reflect the degree of uncertainty for calibration factors. However, the results of the second sensitivity analysis with these alternative calibration factors were not materially different from our main results. We found indications that there is a need for further research about the measurement accuracy of uplink signals and for signals that show a highly variable signal shape under everyday use depending on the data rate of the transmissions such as W-LAN or mobile phone base stations. It seems possible that measurement accuracy depends on the shape of the signal, in particular the pulse duration may play a relevant role.

4.2. Interpretation

Exposure levels were high in trains, tramways and buses, with a high contribution of mobile phone handsets. This was not only due to calls by fellow passengers but also due to the hand-overs during the journey of mobile phone handsets from one base station to the next. Exposure to mobile phone handset radiation in public transport was only slightly lower for persons not owning a mobile phone, showing that passive mobile phone exposure plays an important role in these situations. We found also high exposure levels at airports, but analyses were based on relatively few measurements (5 h in total), and these results should therefore be confirmed in future studies. The low exposures measured at churches and school buildings are explained by the infrequent use of mobile phone handsets at these places. Similarly the lower exposure during night compared to daytime is explained by the smaller contribution of mobile phone handsets. Considerable exposure contrasts were also found between individuals. Explanations for this include difference in exposure at home or at work from fixed site transmitters (mobile phone base stations or broadcast transmitters) and from wireless devices (mobile phone handsets, DECT phones, W-LAN) and different life styles resulting in more or less frequent stays at locations with high exposure levels. Although mobile phone uplink was the major exposure source at most of the locations, mobile phone base stations and cordless phones contributed substantially to total exposure. This is explained by their important role at home and at the workplace where the study participants spent most of their time. Indeed, total weekly exposure correlated well with total exposure at home. For both up- and downlink, in accordance with Bornkessel et al. (2007), exposure to GSM was much more important than exposure to UMTS. UMTS, however, may become more important in the future when large amount of data will be transmitted.

Our data allow assessing the increase of environmental exposure to RF-EMF in the last two decades, which is of concern for part of the population. Prior to the introduction of the mobile phone using the digital GSM 900 and GSM 1800 and the DECT cordless phones in the 1990s (Neubauer et al., 2007), exposure was clearly dominated by radio and TV broadcast. Tell and Mantiply (1980) determined median exposure levels of 0.05 mW/m^2 to ambient radio and TV broadcast. Our outdoor measurements of these sources were somewhat lower but in the same order of magnitude (mean: 0.02 mW/m^2). As in our study exposure to radio and TV broadcast accounted for approximately 10% with respect to total exposure, one could roughly conclude a tenfold increase of exposure to environmental RF-EMF during the last 20 years.

4.3. Implications for research and policy

Our study provides important information for the evaluation of the validity of RF-EMF exposure assessment used in previous studies. We could identify the most relevant exposure contributions and locations with high or low exposure levels, respectively. This is important for interpretation and development of exposure assessment methods. For example, the correlation between bedroom and total exposure was not very strong, suggesting that measurements taken in the bedroom are probably a moderate proxy for total long-term RF-EMF exposure of an individual. This may be particularly the case if only spot measurements are used to determine RF-EMF exposure.

It is reassuring that mean exposures were well below the current threshold levels according to ICNIRP 1998, consistent with other studies that investigated one or several sources of RF-EMF in the everyday environment (Bornkessel et al., 2007; Hutter et al., 2006; Schmid et al., 2007a, 2007b; Schubert et al., 2007; Thomas et al., 2008). Even at places where the highest values were measured in our study, exposure was far below the ICNIRP threshold level. Until now, scientific studies have not provided support for detrimental health-effects due to environmental RF-EMF exposure at such low levels (SCENIHR, 2009). Furthermore, our results indicate that for many individuals a reduction in exposure levels is possible by replacing cordless phones with conventional phones at home. Not using mobile phones or using them less frequently will also reduce exposure. In some situations reductions are more difficult to achieve, particularly if the home or workplace is exposed to a fixed site transmitter, or when traveling.

It has been argued that exposure to environmental fields is not relevant in comparison to exposure from a mobile phone. With respect to exposure at the head, exposure resulting from an operating mobile phone is considerably higher compared to a typical everyday exposure from a mobile phone base station (Neubauer et al., 2007). Regarding whole-body exposure, however, the situation is not so clear. According to a rough dosimetric estimation, 24 h exposure from a base station (1–2 V/m) corresponds to about 30 min of mobile phone use (Neubauer et al., 2007). Our data allow comparing own mobile phone use with base station exposure using the exposimeter readings that were taken at the belt, the backpack or in close vicinity of the body. During own mobile phone use RF-EMF reading of the exposimeter was about 200 times higher than the average base station exposure contribution in self-selected volunteers (4.87 vs. 0.02 mW/m^2). This implies that at the belt, backpack or in close vicinity of the body the mean base station contribution corresponds to about 7 min of mobile phone use (24 h divided by 200).

In the absence of a known biological mechanism we calculated the cumulative average RF-EMF exposure. This is the most common metric for genotoxic agents or for agents with an unknown biological mechanism as it is the case for RF-EMF below the standard limits. Currently we cannot exclude that other exposure metrics are more relevant, like the variability of the field or exposure above a certain threshold (Neutra and Del Pizzo, 2001).

The recruitment of study participants maximized the range of exposure in our study sample and included a substantial number of highly exposed individuals. The self-selected volunteers (Fig. 2) thus probably provide a more reliable estimate of the average exposure and the source contributions in the population of Basel at large. We will examine population level exposure in the next phase of the QUALIFEX study in more detail by inviting a large number of randomly selected individuals to complete a detailed questionnaire on relevant life styles and behaviors. We will then use the data collected in the present study and a propagation model of exposure at home from fixed site transmitters (Bürgi et al., 2008) to model individual exposures.

In conclusion, our study showed that it is feasible to combine diary data with personal RF-EMF exposure measurements. Such data are useful to evaluate RF-EMF exposure during activities of daily living. Personal weekly exposure measurements are reproducible and we found considerable exposure contrasts between persons as well as spatial and temporal variability. These are prerequisites to develop an exposure assessment method for future research. In-depth knowledge of the exposure situation of the general population is helpful to reduce exposure misclassification in future epidemiological studies.

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5 Development of an RF-EMF exposure assessment method

Article 4: A model for radiofrequency electromagnetic field predictions at outdoor and indoor locations in the context of epidemiological research

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A Model for Radiofrequency Electromagnetic Field Predictions at Outdoor and Indoor Locations in the Context of Epidemiological Research

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We present a geospatial model to predict the radiofrequency electromagnetic field from fixed site transmitters for use in epidemiological exposure assessment. The proposed model extends an existing model toward the prediction of indoor exposure, that is, at the homes of potential study participants. The model is based on accurate operation parameters of all stationary transmitters of mobile communication base stations, and radio broadcast and television transmitters for an extended urban and suburban region in the Basel area (Switzerland). The model was evaluated by calculating Spearman rank correlations and weighted Cohen's kappa (κ) statistics between the model predictions and measurements obtained at street level, in the homes of volunteers, and in front of the windows of these homes. The correlation coefficients of the numerical predictions with street level measurements were 0.64, with indoor measurements 0.66, and with window measurements 0.67. The kappa coefficients were 0.48 (95%-confidence interval: 0.35–0.61) for street level measurements, 0.44 (95%-CI: 0.32–0.57) for indoor measurements, and 0.53 (95%-CI: 0.42–0.65) for window measurements. Although the modeling of shielding effects by walls and roofs requires considerable simplifications of a complex environment, we found a comparable accuracy of the model for indoor and outdoor points. Bioelectromagnetics 31:226–236, 2010. © 2009 Wiley-Liss, Inc.

Key words: non-ionizing radiation; exposure assessment; electromagnetic fields; exposure model; mobile phone; mobile communication base station; broadcast transmitter; epidemiology

INTRODUCTION

In order to assess possible long-term effects of low levels of non-ionizing radiation in epidemiological studies, it is necessary to determine the exposure to radiofrequency (RF) electromagnetic fields (EMF) for all study participants [Neubauer et al., 2007]. Exposure to RF-EMF is caused by many different sources, for example, mobile phone handsets, cordless telephones, wireless computer components, and also stationary transmitters for mobile communication and broadcast services. While useful proxies exist for the exposure by some of these sources (e.g., duration of phone calls with a mobile phone, presence of a cordless telephone and intensity of its use), no simple proxies exist for

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stationary transmitters. It has been repeatedly pointed out in literature that simple proxies such as the distance to the nearest base station are of no use for exposure assessment [Neubauer et al., 2007; Schubert et al., 2007]. In principle, measurement of the exposure of individuals can today be performed relatively easily and accurately with personal exposure meters (''exposimeters''). However, its application is still limited in epidemiological research for large collectives and it may be prone to manipulation when study participants deliberately put it at highly exposed places. Thus modeling of exposure is a useful alternative to personal measurements.

In the Qualifex study (Health related quality of life and RF-EMF exposure: Prospective cohort study [Röösli et al., 2008], www.qualifex.ch) we aimed at combining personal RF-EMF measurements with RF propagation modeling to identify exposure relevant factors and to develop a method for RF-EMF exposure assessment that can be applied to a large collective.

Many propagation models for RF-EMF have been developed for network planning and site selection, for example, by the International Telecommunications Union (ITU) and the telecom industry. Examples are the recommendation ITU-R P.1546-1 [ITU, 2003] and the COST (European Cooperation in Science and Technology)-Walfisch-Ikegami model (COST-WI) [Geng and Wiesbeck, 1998; Kürner, 1999]. Models for the exposure of the general public to RF-EMF have been published by Anglesio et al. [2001], Lehmann et al. [2004], Zmyslony et al. [2006], Bornkessel et al. [2007], and Schubert et al. [2007]. A model for application in an epidemiological study has recently been published by Neitzke et al. [2007].

For Qualifex, we developed a geospatial model that predicts RF-EMF from fixed site transmitters, such as mobile phone base stations and broadcast transmitters, using available data for these transmitters and also the three-dimensional environment including topography and buildings [Bürgi et al., 2008]. Our propagation model has been shown to adequately predict RF-EMF at outdoor locations. However, so far evaluation of indoor predictions has not been done. Prediction of indoor exposure is expected to be more challenging because RF-EMF interacts with housing characteristics such as geometry and type of walls, windows, interior structure, and furnishings. To obtain this information in detail is difficult even for a single building; for large study areas it is unfeasible, and simplifications have to be made. As a first-order approximation, we used a constant average damping coefficient for all building walls and roofs for the work presented here. We then tested whether such a simplification still allows sufficiently accurate predictions of indoor RF-EMF. In a second step we also tested whether additional information provided by the study participants about their apartment would improve the indoor predictions.

The aim of this paper is to compare modeled RF-EMF from fixed site transmitters with outdoor and indoor measurements. The indoor measurements were taken in the bedrooms of study participants; the outdoor measurements were taken both at street level and in front of the bedroom windows of study participants. In addition, we examined the dependence of the results on different choices of model input parameters by carrying out a sensitivity analysis.

Ethical approval for the conduct of the study was received from the Ethical Commission of Basel (EK: 38/07).

METHODS

Exposure Metric

When assessing health effects of RF-EMF, it is a priori unclear what kind of radiation parameters in terms of frequency, modulation, etc., might cause an effect. In Qualifex, we use the electric field strength of the total RF-EMF (integrated over all frequency bands of interest) as exposure metric. Because our model considers only fixed site transmitters, we use the term ''total field strength'' (E_{total}) in this paper in a more restrictive sense, that is, for the field strength integrated over the frequency bands covered by the model

$$E_{\text{total}} = \left(\sum_i E_i^2 \right)^{1/2}$$

where the summation is over the contributions E_i of all bands of broadcast, paging services, and mobile communications downlink given in Table 1. The contributions of DECT telephones, WLAN, and mobile phone uplink frequencies were not included in the analysis reported here.

Propagation Model Description

The propagation model described in Bürgi et al. [2008] is based on the simulation software NISMap and a database of fixed transmitter data compiled by the Basel Air Quality Agency, supplemented by actual transmitter operation parameters at given time points obtained from a database of the Swiss Federal Office of Communications (OFCOM). The study area covers the city of Basel and the Swiss part of the region.

The NISMap model integrates the location and transmission patterns of all transmitters with the three-dimensional geometry of the urban environment,

TABLE 1. Frequency Bands Covered by the Propagation Model

Band	Radio service	Frequency range (MHz)
VHF II	FM radio	87.5–108
Paging	Paging services	147–148
VHF III	TV band III	174–223
DAB (channel 12)	Digital audio broadcast	223–230
Tetrapol	Police, emergency services	390–393
UHF IV and V	TV band IV and V	470–862
GSM-Rail	Mobile communication, railway	921–925
GSM 900	Mobile communication (downlink)	925–960
GSM 1800	Mobile communication (downlink)	1805–1880
UMTS	Mobile communication (downlink)	2110–2170

considering, for example, shielding effects by buildings and topography. As a baseline we use the propagation algorithms of COST-Walfisch-Ikegami [Kürner, 1999] for mobile phone base stations and ITU-R P.1546-1 [ITU, 2003] for radio and TV broadcast stations. The propagation algorithms are semi-empirical. Basically, they give a distance law for the electric field strength as a function of transmitter power, frequency, and propagation conditions (e.g., line-of-sight, LOS, or non-line-of-sight, NLOS). The propagation model produces point values which are to be understood as local averages, that is, also averaged over a possible local interference pattern.

Compared to the model previously described by Bürgi et al. [2008], the following modifications were made: (i) The actual antenna downtilt from the OFCOM database was used instead of the previously used worst-case antenna patterns for angular sectors where the site permission database had a range of possible downtilts for antennas with adjustable electrical tilt (e.g., from 0° to –6°). (ii) The COST-WI algorithm was modified so that it can also be used for heights above the original validity range (3 m). This was achieved by replacing a global parameter for the average building height by an average over the actual height of buildings blocking a particular line-of-sight. This correction is essential when calculating the propagation under NLOS conditions for points at elevated heights.

The damping by roofs and walls of buildings was modeled with a single average damping coefficient. We used a baseline value of 4.5 dB, corresponding, for example, to a combination of concrete (15 dB) and 1/3 transparent window area at normal incidence, or approximately to wood or brick at normal incidence [Berg, 1999]. Inside buildings, an additional damping of 0.6 dB/m was added to take into account interior walls, floors, and furnishings. Damping coefficients for the different materials were taken from Berg [1999].

The transmitter powers in the OFCOM database correspond to base stations transmitting at maximum installed power. In reality, the radiated power of a GSM or UMTS base station varies as a function of communication traffic. For GSM, we use duty factors derived from the data in Lehmann et al. [2004] to describe the ratio of the average transmitted power during daytime (06–22 h) to the maximum power. These factors are used as functions of the number of transmitters per antenna, for example, factors of 1.0, 0.65, and 0.48 for one, two, or three transmitters, respectively. For UMTS we use a duty factor of 0.15.

Input Data

The propagation model depends on the availability of accurate and complete transmitter data. In Switzerland, a site data sheet with detailed technical specifications has to be supplied to the authorities in order to obtain a permit to build or operate a base station or broadcast transmitter. Our dataset was assembled from such data sheets by the Air Quality Agency of Basel. These data were then supplemented with the actual operational transmitter powers, number of GSM channels, and antenna downtilts imported from a database of mobile communication base stations maintained by OFCOM. All data were crosschecked and validated by the Air Quality Agency of Basel. The model database keeps track of the transmitter history, for example, transmitters going in and out of operation, and by using operation parameters for different times the model can produce field calculations for selected dates. The transmitter data as of November 2007 were imported and subsequently used for comparison with measurements made at the homes of study participants between April 2007 and February 2008. A table listing all the necessary input data and their sources is given in Bürgi et al. [2008].

One of the lessons learned from previous applications of the propagation model is that a good geometrical description of buildings in the model region is a critical input, even if only outdoor points are considered in the calculation, because the difference between line-of-sight and non-line-of-sight conditions affects the results by orders of magnitude. The 3D city model of Basel was previously incorporated into the model database. For the suburban and rural regions not covered by this city model, the database was completed with a 3D block model of buildings based on digital floor plans and the building heights estimated from a dataset containing the number of floors. The height above the ground for a study participant's home was calculated as the floor number times an average height (typically 2.6 m) plus 1.5 m.

The coordinates of the study participants' bedrooms were derived manually from digital maps after visiting the study participants and locating the bedroom within the building (bedroom coordinates). Alternatively, coordinates for each building were obtained from the Federal Office of Statistics. These coordinates are from a database linking each address in Switzerland to a coordinate (address-based coordinates).

Measurements

We used three sets of measurements taken with a NARDA SRM-3000 radiation meter (NARDA Safety Test Solution, Hauppauge, NY) to compare the propagation model output: (1) a set of outside values ($n = 113$ points) at street level accumulated by the Air Quality Agency, (2) a set of indoor measurements in the bedrooms of participants of the Qualifex study ($n = 133$), and (3) a corresponding set of measurements outside the windows of the bedrooms ($n = 131$). From this point on, we will refer to these datasets as ''street,'' ''home,'' and ''window.'' The street level measurement locations were chosen to represent a variety of exposure conditions, most were near base stations, under both line-of-sight and non-line-of-sight conditions. The home and window measurements were made at homes of individuals who had volunteered for the Qualifex study ($n = 107$), supplemented by a number of homes of study participants that were actively recruited because we expected them to be highly exposed because of proximity to a base station or radio/television transmitter ($n = 26$). Because this situation is generally rare in a random population sample, we oversampled highly exposed individuals in order to obtain the full range of exposure conditions in our study area. The selection procedure is explained in detail in Frei et al. [2009]. The measurements were taken as temporal averages of the electric field strength (in V/m) with the root-mean-square (RMS) averaging mode of the radiation meter. The acquisition time for a single measurement was 30 s. The measurements were frequency selective, but only the bands included in the model (Table 1) were considered in the analysis. We used an isotropic three-axis antenna mounted on a short pole, which was held as far away from the operator as possible. According to the instrument datasheet, the extended measurement uncertainty of the SRM-3000 in the frequency range 85–2700 MHz is +2.6/−3.7 dB (+82/−57% in power density or ±35% in electric field strength; 95% confidence interval, CI). For the measurements we adapted methods proposed by CENELEC (EN 50492) [2008]. Based on an exploratory measurement campaign, we found that seven measurement points per room provide stable estimates of the average exposure. The first three points were chosen in the center of the room at 1.1, 1.5, and 1.7 m above the floor. Four additional points were arranged in a rectangle, each 1 m from the center toward a corner of the room, 1.5 m above ground. An analogous seven-point average was used for the street dataset (a central point at 1.1, 1.5, 1.7 m plus four additional points at 1.5 m height in the four compass directions). For the measurements taken in front of bedroom windows, we used only three measurement points (left, center, and right) approximately 1–1.5 m in front of the open window. The values used in the datasets ''street,'' ''window,'' and ''home'' are the respective seven- or three-point RMS averages.

While our calculated field strengths are for average daytime conditions, the measurements give instantaneous values. For mobile communications, the transmitted power varies as a function of the communication traffic. Routinely collected monitoring data from Air Quality Management Agency of Basel have shown that variations of hourly averages are moderate (typically <20%), but short-time variability is larger. For the GSM bands, the ratio of the maximum to minimum power is equal to the number of installed transmitters per cell (typically 2–4), so short-time variations of the field strengths in the range of 1.4–2 are to be expected. Therefore, the comparison of model and measurement can only be made in a statistical sense by considering averages over many measured points.

Data Analysis

When comparing model results and measurements, we calculated and tabulated the following statistical properties: the mean deviation of the model from the measurements, the percentage of points F_2 where the agreement between modeled and measured electric field strengths is within a factor of 2, the percentage of points F_4 where the agreement is within a factor of 4, the linear (Pearson) correlation coefficient ρ, and the Spearman rank-order correlation coefficient ρ_s. Chance-corrected agreement was evaluated by weighted Cohen's κ (kappa) statistics using a classification of the data distributions into three tertiles with linear weights, counting classification into adjacent categories as 50% agreement, otherwise as complete disagreement. In one comparison, the value of κ was also calculated for a classification into only two classes, with the same cut-off as in Neitzke et al. [2007]. For this case, the sensitivity (proportion of true highly exposed, indentified as such) and specificity (proportion of true lowly exposed, indentified as such) of the classification were also calculated and compared [Kirkwood and Sterne, 2003].

We tested whether our crudely built damping model could be improved by using additional information of the study participants' homes that we obtained from questionnaires, such as the floor number, date of construction, type of wall (concrete or other), type of roof (flat or gabled), type of dwelling (single family home or apartment building), and type of window frame (metal, synthetic material, or wood). We computed multiple linear regression models with the log-transformed ratio between calculated and measured power flux density as the dependent variables, and the housing characteristics as the explanatory variables. We used a stepwise variable selection procedure based on likelihood ratio tests and Akaike's Information Criteria (AIC) to determine relevant housing characteristics.

Sensitivity Analysis

In order to determine the sensitivity of the model to different selections of propagation algorithms and model parameters, we calculated model variants by varying all input parameters whose influence was not a priori evident: the propagation algorithm, damping coefficients, parameters of the COST-WI-NLOS equations, use of building data, and address-based coordinates (instead of bedroom coordinates). For all model variants, we compared the results to the same measurements as for the baseline model.

RESULTS

As a first result, a color-coded field-strength map was calculated for the study area, which covers an area of 179 km^2 with a population of 379,000. The map consists of $3 \times 3\,km^2$ tiles covering the study area, with grid cells of 5 m resolution. The map was then used to select areas of high field strengths in order to actively recruit a few study participants, because high exposures can only be found relatively close to transmitters, and even then, typically only at the upper floors of a building.

Overview of Measurement Results

The average measured total RF-EMF (arithmetic mean) was 0.37 V/m at the 113 "street" locations, 0.13 V/m in the 133 "home" measurements, and 0.25 V/m at the 131 "window" measurements. The relative contribution of the different radio services (in terms of power density) to the total measured field strength is shown in Figure 1. The dominant contribution in all three datasets is from GSM 1800. In the "street" data, GSM 900 is of the same magnitude, while FM radio and UHF TV contribute very little. In the "window" and "home" data, FM radio is of the same order as GSM 900 (15–20%), and UHF TV contributes some 6%. This enhancement of radio and TV compared to the "street" data is the result of active recruitment of volunteers near a strong radio/TV transmission tower. The contributions of paging and DAB are about 1%, while contributions from VHF III, Polycom (Tetrapol), and GSM-Rail are negligible.

Wall Attenuation

The ratio of the field strength in rooms to the field strength outside the window of these rooms is obtained by combining the "home" and "window" data; the result is shown in Figure 2. The values range from just below 0.1 to 1.99. For interpretation, bear in mind that we conducted spot measurements and that transmitter powers may have changed between the indoor and outdoor measurement. In addition, the spot measurements may be subject to reflection or interference. Seven out of 130 ratios are larger than one. At five of these locations, the window is directed away from the nearest base station (i.e., an outgoing wave instead of an ingoing one); in one case the base station is directly on top of the house. For the most extreme case (ratio = 1.99) we could not find a plausible explanation. Considering only ratios smaller than one, the RMS value of the ratios is 0.59 (4.6 dB). Corresponding mean ratios for individual bands are shown in Table 2. The

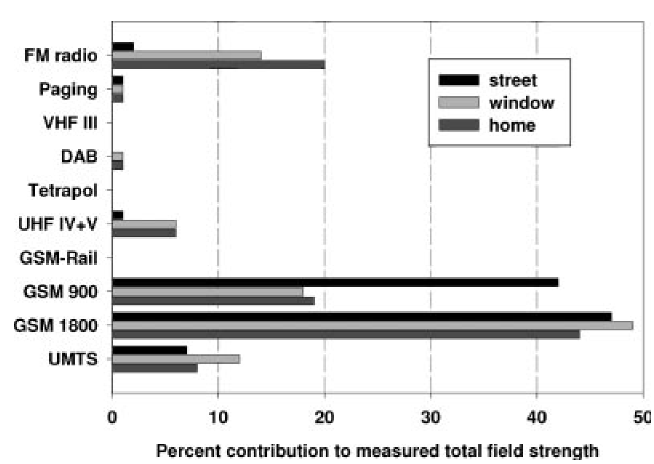

Fig. 1. Contributions to the average measured total field in the three datasets "street," "window," and "home" (in percent).

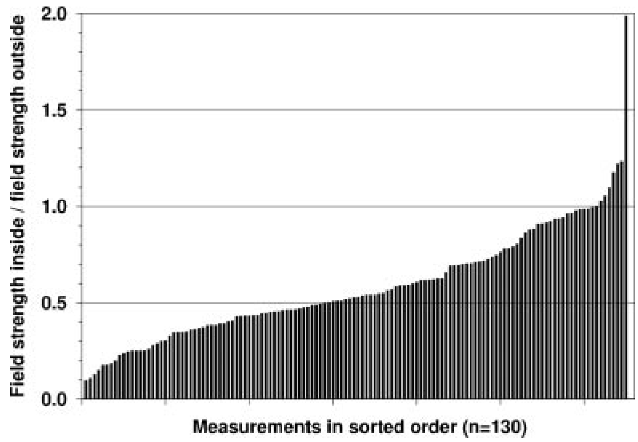

Fig. 2. Distribution of the ratio of the field strength outside of the window and inside the room, for all cases where both measurements were available (130 pairs of measurements). The ratios range from 0.1 to just below 2.

table shows a trend to higher damping with increasing frequency, except for the value for UMTS.

Comparison of Measurement and Calculation

The comparison of the calculated and measured total field strengths is shown in Figure 3. The calculated field strength is plotted versus the measured field strength; the three datasets are each shown in their own panel. All three scatter-plots show a variance of the data over approximately two orders of magnitude. Table 3 summarizes the results of model and measurements for the three datasets. The field strength is highest for the ''street'' data, and lowest for the ''home.'' The average field strength is most strongly overestimated for the ''street'' data and somewhat underestimated for the ''home'' data; the ''window'' data are again between the two. The fraction F_2 of data points showing an agreement of better than a factor of 2 (in field strength) ranges from 63% (street), over 61% (windows) to 51% (home). F_4, the fraction of points with agreement within a factor of 4 varies less: it ranges from 92% (street) to 89% (home). The linear (Pearson) correlation coefficient (ρ), which is mainly influenced by the few highest values in the dataset, is highest for the ''home'' data. The Spearman's rank-order correlation coefficient ρ_s lies between 0.64 and 0.67 for all three datasets. Finally, we also calculated the parameter κ, the degree of agreement between classifications of the modeled and measured values, into three tertiles using linear weights. We found values of 0.44 (homes) to 0.53 (windows). A comparison of the relative errors for the individual frequency bands is shown in Figure 4. For the dominant GSM bands, the model is on average slightly high, while other bands like FM radio, TV IV and V, and also UMTS are underestimated by 20–60%.

In the attempt to improve our crude building model by considering housing characteristics, we found two factors that were significantly associated with the ratio between calculated and measured electric field strengths: Our model overestimates the electric fields in buildings with concrete walls by a factor of 1.7, and underestimates the field in older houses by a factor of 1.4. However, the two variables can only account for 10% of the unexplained variance in the data, and recalculating the electric fields in the respective houses by using adjusted damping factors did not improve the Kappa statistics (data not shown).

Sensitivity Analysis

We calculated a number of alternative models with different propagation algorithms and model parameters to analyze the sensitivity of the model to varying assumptions. The results of these models were then compared to the baseline model (labeled A1). In models B1 and B2, we used different propagation algorithms. Model B1 uses the double power law [Bürgi et al., 2008] for base stations instead of COST-WI; model B2 uses the double power-law for broadcast transmitters instead of ITU-1546. Model variants C1–C5 test the influence of building damping parameters; in C5, a frequency dependent damping coefficient proportional to $f^{0.2}$ (determined from the data in Table 2) was used. In models D1 and D2 the parameters of the COST-WI-NLOS models were varied; in model D3, a fixed average building height

TABLE 2. Root-Mean-Square Ratios of Electric Field Inside Rooms (E_{in})/Outside the Windows (E_{out}), Derived Damping Factors ($-20\log(E_{in}/E_{out})$ in dB), Interquartile Interval, and 5–95th Percentile Interval of E_{in}/E_{out}

Radio service	Root-mean-square ratio of E_{in}/E_{out}	Derived damping factor (dB)	Interquartile interval (25–75%) of E_{in}/E_{out}	5–95% interval of E_{in}/E_{out}
FM radio	0.80	1.9	0.52–0.90	0.33–1.15
GSM 900	0.61	4.3	0.37–0.71	0.19–0.96
GSM 1800	0.58	4.7	0.30–0.70	0.15–0.98
UMTS	0.65	3.7	0.33–0.81	0.16–1.05
Total field	0.59	4.6	0.38–0.70	0.19–0.97

The seven points where the total electric field was higher inside than outside were excluded from this table.

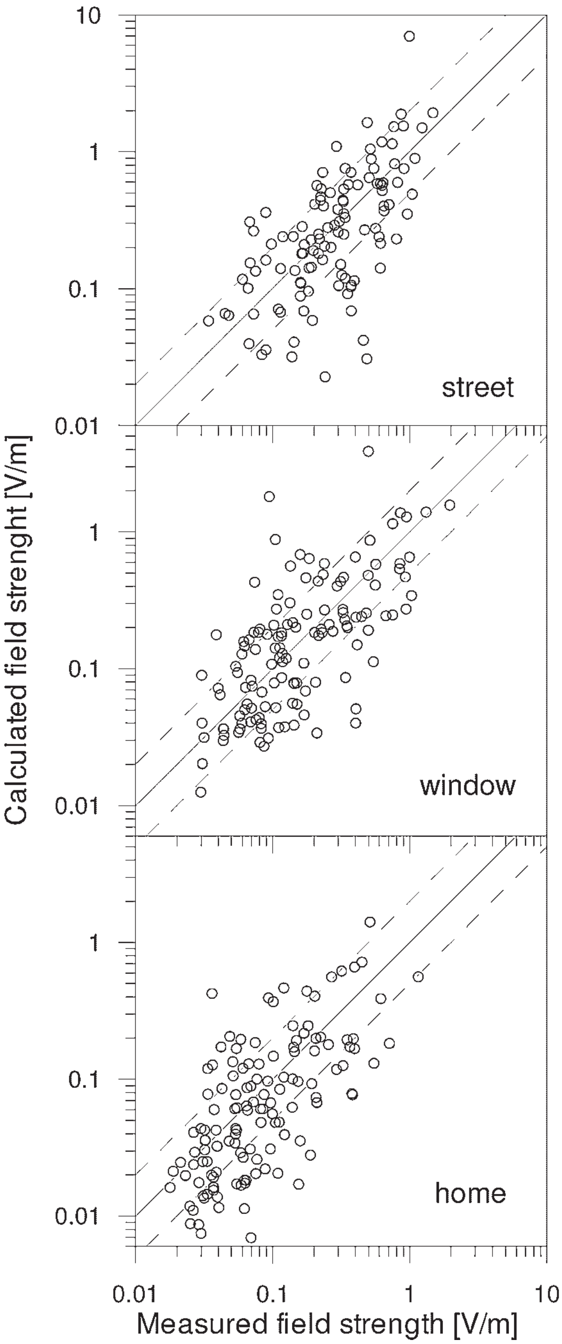

Fig. 3. Scatter plots of the calculated total field strength versus measured total field strength for the three datasets "street," "window," and "home." Points on the solid diagonal have perfect agreement of model and measurement; the dashed lines indicate a deviation of a factor of 2 ("total field" refers to the field integrated over the modeled frequency bands given in Table 1).

of 10 m was used in the COST-WI equations, instead of the average along the line-of-sight as determined from the building model (as described under Methods Section). Model E1 completely neglects buildings, E2 uses antenna tilt sectors instead of the correct operational values, E3 has a doubled ERP (equivalent radiated power) duty factor for UMTS, E4 uses address-based coordinates instead of the accurate bedroom coordinates for the "home" dataset, and E5 excludes the data of the 26 actively recruited participants who live close to transmitters. Finally, we compared a "naïve model" (F), which uses the inverse distance to the nearest transmitter as exposure proxy.

The results of the sensitivity analysis are summarized in Table 4. The differences are generally subtle, with the noted exception of D3, E1 and, as expected, the naïve model (F). In D3, tall buildings are not treated correctly and in E1, buildings are neglected completely. In these cases, not only the building damping is treated incorrectly but also the distinction between LOS and NLOS conditions, leading to order-of-magnitude errors in some cases. Somewhat surprising, the use of the correct antenna tilt values gives only a marginal improvement compared to the "worst-case" antenna tilt sectors (E2) for the "window" and "home" datasets.

The performance of the naïve model (F) is very poor, with the exception of the "street" dataset, which is probably due to the fact that we conducted more than one measurement of one specific base station. Typically, measurements close to the base station were LOS, whereas more distant measurements were NLOS (e.g., behind a house).

DISCUSSION

We found satisfactory agreement between the modeled values and sets of measurements taken at street level, in front of the window and in the bedroom of study participants. Most interestingly, the extent of agreement was similar for indoor data compared to outdoor data, despite increased complexity of the environment. The sensitivity analysis has shown that the model is robust and quite insensitive to changes in model parameters such as propagation algorithm, damping coefficients and parameters of the COST-WI model. It is important to note that we did not fit a model specifically to our measurements. Instead, we used established semi-empirical propagation algorithms and parameters determined in a much wider setting (COST-WI and ITU) than our study area.

The exposure at an indoor location is strongly modified by absorbing and reflecting walls and obstacles. The reflection and damping of radiation by an obstacle (e.g., wall, roof, or window) depends on the frequency and angle of incidence of the wave, the material, and thickness, and maybe more importantly the coating and sheathing of the obstacle, and it can vary over many orders of magnitude. While windows are

TABLE 3. Comparison of Modeled Total RF-EMF Field-Strength With Three Sets of Measurements

Measurement set	Street data (outdoor)	Window data (outdoor)	Home data (indoor)
Average measured field (V/m)	0.37	0.25	0.13
Average calculated field (V/m)	0.45	0.28	0.12
Number of values n	113	131	133
Mean relative difference (model − measured)/(average measured) and 95% CI	+22% (−10%, +54%)	+12% (−15%, +39%)	−4% (−25%, +17%)
Agreement within factor of 2 (F_2)	63%	61%	51%
Agreement within factor of 4 (F_4)	92%	91%	89%
Correlation coefficient ρ (Pearson)	0.54	0.51	0.57
Rank order correlation coefficient ρ_s (Spearman)	0.64	0.67	0.66
Kappa (tertiles[a], linear weights) κ, and 95% CI	0.48 (0.35, 0.61)	0.53 (0.42, 0.65)	0.44 (0.32, 0.57)

Average measured and average calculated refers to the arithmetic mean. F_2 is the fraction of cases where model and measurement agree within a factor of 2; F_4 is the fraction of cases where they agree within a factor of 4 (in field strength).
[a]The cut-offs between the tertiles were 0.19 and 0.37 V/m for street measurements, 0.09 and 0.21 V/m for window measurements, and 0.05 and 0.10 V/m for indoor measurements.

mostly transparent (to RF-EMF), materials like wood and brick are semi-transparent, steel-reinforced concrete is a strong absorber and a metal wall is a quasi-perfect absorber/reflector. But windows can be metal-coated, for example, to reflect thermal infrared as a measure to conserve energy, and could possibly also reflect RF-EMF [Berg, 1999]. In principle, one could introduce the physically correct damping factors in a model. However, this would require an enormous effort to obtain such detailed building data. Thus from a practical point of view, we had to simplify the complicated mixture of walls, roofs, and windows into average building damping properties, and a priori it was unclear whether this simplification can provide meaningful results. From the distribution of the damping values (Fig. 2) and the fact that the agreement of the model with the measurements is only slightly worse (Table 3) inside (“home”) than outside (“street” and “window”), we conclude that the variation of building-damping properties in our sample is moderate, and that the first-order assumption of a constant wall damping gives meaningful results. The sensitivity analysis shows that the model predictions could still be improved with a different choice of damping coefficients, for example, a damping of approximately 3 dB/wall and a lower volume damping coefficient. But it is important to note that the actual value is not important when the primary aim is a ranking of the exposure for determining high and low exposed homes, because we use the same damping coefficient for all buildings.

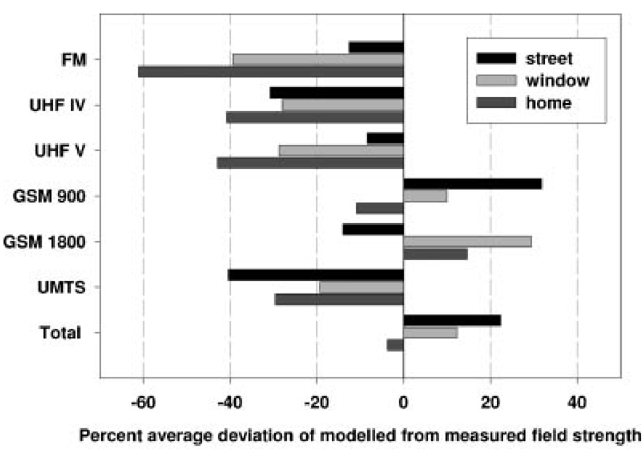

Fig. 4. Relative deviation of the modeled field strength for the baseline model for individual frequency bands. Plotted values are averages of ((model − measurement)/measurement). Bands without significant contributions have been omitted.

Introducing a frequency dependent damping (lower for low frequencies) improved the agreement at the FM-radio frequencies, but the overall result was not much different and there remains a discrepancy between model and measurement at FM-radio frequencies. Similarly, taking into account additional building data that could be obtained from the study participants, such as the presence of concrete walls or the building date, improved the model further although not in a substantial way. This may be because it is difficult for laymen to give accurate data about building characteristics.

In our model we extended the COST-WI model to heights above the original validity of 3 m by using the actual average building height in the COST-WI equations for NLOS conditions. The good performance of the model for the “window” and “home” datasets suggest that this extension is justified. The bad performance of model variant D3 demonstrates that this extension is also necessary, and that a fixed average building height may no longer be used when receptor points can be above this average height. In addition, the sensitivity analysis has again shown that

TABLE 4. Results of the Sensitivity Analysis

Model variant (↓)	Average relative difference (model − measured)/in % of average measured			Agreement within factor 2 F_2 (%)			Rank-order correlation τ_s			Kappa (tertiles with linear weights)		
Dataset (→)	Street	Window	Home	Street	Window	Home	Street	Window	Home	Street	Window	Home
A1: baseline	22	12	−4	63	61	51	0.64	0.67	0.66	0.48	0.53	0.44
B1: powerlaw for mobile communication	33	25	23	59	51	55	0.65	0.66	0.68	0.48	0.45	0.49
B2: powerlaw for broadcast	20	14	−2	61	63	50	0.65	0.68	0.66	0.50	0.52	0.41
C1: wall/roof damping 3 dB	23	14	15	62	61	58	0.64	0.68	0.67	0.48	0.52	0.46
C2: wall/roof damping 6 dB	22	12	−20	62	60	49	0.64	0.67	0.65	0.48	0.52	0.44
C3: volume damping 0.4 dB/m	22	13	11	63	62	55	0.64	0.68	0.66	0.48	0.53	0.43
C4: wall 3 dB, roof 6 dB	23	13	8	62	61	59	0.64	0.68	0.67	0.48	0.53	0.48
C5: damping frequency dependent	23	14	0	62	63	53	0.64	0.68	0.67	0.48	0.54	0.48
D1: COST-WI: street width 25 m	24	18	−1	62	63	57	0.63	0.68	0.67	0.48	0.55	0.46
D2: COST-WI: building distance 30 m	24	17	−1	61	63	54	0.63	0.68	0.67	0.48	0.55	0.44
D3: COST-WI: building height 10 m	27	117	62	68	50	51	0.65	0.56	0.53	0.50	0.38	0.31
E1: no buildings	69	120	341	56	27	9	0.50	0.51	0.44	0.34	0.35	0.27
E2: antenna tilt sectors	40	28	9	58	59	54	0.62	0.66	0.69	0.46	0.48	0.48
E3: UMTS ERP duty factor 0.3	24	16	−2	61	60	52	0.65	0.67	0.66	0.50	0.52	0.43
E4: address-based coordinates			−5			50			0.64			0.43
E5: actively selected points excluded								0.62	0.58		0.45	0.41
F: inverse distance law							0.50	0.28	0.18	0.34	0.26	0.09

good building data are an essential requirement (model E1).

When comparing the model to measurements, we treated the measurements as a "gold standard." However, RF-EMF measurements also have considerable uncertainties; for the SRM-3000, these amount to $\pm35\%$ in electric field strength. In addition, the measurements were of short duration and contain fluctuations due to short-time variations of transmitter power, and in spite of the seven-point averaging, they might still be affected to some degree by spatial interference patterns. The fact that we compared spot measurements to the modeled time-averages is a source of scatter in the data distribution and might also partly explain why the outdoor comparisons are not much better than the indoor comparisons, and why the sensitivity analysis often produced small differences between models.

We will apply this model to estimate the average exposure for a period of a few months. A recent measurement campaign showed that weekly average personal RF-EMF exposure in the bedroom remained relatively stable over a period of several months: Repeated measurements of 29 volunteers yielded a mean difference of only 0.023 V/m between the first and second measurement, which took place 3–41 weeks later (standard deviation: 0.051 V/m) [Frei et al., 2009]. In order for the model to be applicable for longer-term exposure assessment, the input data could be updated periodically to keep track of the evolution of communication infrastructure. Thus in principle the model could be useful for long-term exposure assessment, although this still needs to be validated. In the long run it is not yet clear how relevant exposure contribution from fixed transmitters is, compared to other sources such as use of wireless communication devices.

During the course of this study we have identified a number of issues for model accuracy. A first major difficulty is keeping the building database accurate and up-to-date, for example, to take into account newly constructed houses.

A second source of major errors is the height estimate of the study participants' home. We had to estimate the height above ground from the floor number and an average height per floor. Unfortunately, this procedure produces the largest uncertainties at elevated floors where the points may be close to a beam radiated from an antenna on a neighboring roof, and precision would be mostly required because these beams are typically very narrow in elevation (a few degrees). We plan to improve on this by not only asking the floor number of the apartment, but also the total number of floors (including attic) in future questionnaires, which will allow us to more accurately estimate the height per floor from the known building height and the total number of floors. With this, we should be able to reduce the uncertainty of the z-coordinate of upper floors. The wall damping could be further improved by incorporating available information such as the building type and date of construction but this has to be tested first in an independent dataset.

When modeling RF-EMF exposure of individuals at their homes or workplaces, the acquisition of precise enough coordinates becomes a practical difficulty when these have to be derived from addresses and questionnaire data alone. For the transmitters, accurate coordinates were available from the transmitter data base. For the homes of the study participants, we manually extracted coordinates by considering the position of the bedroom within the building. Address-based coordinates for the study participants, which are more conveniently obtained for a large collective, resulted in a decrease of the agreement between model and measurement, but the decrease was small. The results for the UMTS model were on average, about 30% lower (in field strength, see Table 4). This could be corrected by increasing the duty factor $f = \mathrm{ERP(average)/ERP(max)}$ from our low value of $f = 0.15$ to 0.3 for daytime conditions (06–22 h). The factor of 0.15 seems more appropriate to nighttime conditions [B. Eicher, personal communication]. This would give an average whole-day duty factor of 0.25, as proposed by Lehmann et al. [2004]. Because the relative contribution of UMTS to the total RF-EMF will conceivably increase in the future, a more accurate determination of the UMTS power duty factor should be attempted in future models.

From Figure 3, we can see that the model has a tendency to overestimate the larger field strengths (and also the average for the dominant GSM bands) and underestimate the weaker fields. Possible explanations might be damping by vegetation (trees) for the high values, and reflections under NLOS conditions for the low values; these effects are not accounted for in the model.

In a recent paper, Neitzke et al. [2007] also introduced a propagation model with the aim of application in an epidemiological study. The main difference to the work reported here is that Neitzke et al. concentrated on mobile phone base stations alone, and because of the restricted availability of actual transmitter data they had to rely on typical values for antenna patterns, downtilt, and transmitter power, while we calculated for mobile communication and broadcast services and had actual transmitter data available. Their sample was considerably larger, with $n = 610$ indoor measurements compared to our 133. They reported kappa values, sensitivities and specificities for an

TABLE 5. Comparison With Results of Neitzke et al. [2007]

Parameter	This work, inside homes (95% confidence interval)	Neitzke et al. [2007]
Kappa (total field)	0.54 (0.38–0.70)	0.50
Sensitivity	0.63	0.56
Specificity	0.90	0.93
Kappa (GSM 900)	0.60 (0.34–0.84)	(~0.50)
Kappa (GSM 1800)	0.60 (0.35–0.80)	(~0.50)
n (number of points)	133	610

Two-level classification with a cutoff at $E = 0.137$ V/m (50 μW/m^2). The values from Neitzke et al. are the average over all building categories.

exposure cut-off at 0.137 V/m (50 μW/m^2). We calculated the same quantities for our "home" dataset and the comparison is shown in Table 5. Most of the values are quite similar. When they applied their model in a more comprehensive epidemiological study [Breckenkamp et al., 2008] with less accurate coordinates for transmitters and receptors, the authors concluded that the model can only be applied in epidemiological studies when the uncertainty of the input data is considerably reduced. This is in agreement with our finding that accurate transmitter input data, a reliable building model and accurate coordinates for both transmitters and receptors are a prerequisite of the propagation model. However, we found only a modest deterioration when introducing address-based coordinates for the receptor points (model E4). Thus we conclude that precise coordinates are more important for transmitters than for receptors. Base station antennas are systematically placed at points with good visibility from their neighborhood, for example, on edges of flat roofs. Replacing the correct antenna coordinates by address-based coordinates in such cases would typically put the antennas at the center of the building, and the neighboring buildings would change from LOS to NLOS conditions, causing an orders of magnitude difference in the EMF strength. In contrast, the receptor points are distributed randomly, and changing the coordinates by a few meters is expected to introduce smaller changes of the wave propagation conditions.

Our modeling procedure for Basel and the surrounding area can, in principle, be generalized to any other region where the necessary input data (transmitters, buildings, topography) are available. The results from our sensitivity analysis provide a clue which input data are crucial and have to be obtained with sufficient precision. In conclusion, we find that we have extended a model for RF-EMF exposure that performed well at outdoor locations and can also successfully predict exposure at indoor locations.

Despite all the simplifications, the performance for indoor points is only slightly reduced compared to outdoor points. The model is robust and quite insensitive to the exact choice of parameters and it is well suited to classify exposure levels for application in an epidemiological study.

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Article 5: A prediction model for personal radio frequency electromagnetic field exposure

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A prediction model for personal radio frequency electromagnetic field exposure

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ABSTRACT

Radio frequency electromagnetic fields (RF-EMF) in our daily life are caused by numerous sources such as fixed site transmitters (e.g. mobile phone base stations) or indoor devices (e.g. cordless phones). The objective of this study was to develop a prediction model which can be used to predict mean RF-EMF exposure from different sources for a large study population in epidemiological research. We collected personal RF-EMF exposure measurements of 166 volunteers from Basel, Switzerland, by means of portable exposure meters, which were carried during one week. For a validation study we repeated exposure measurements of 31 study participants 21 weeks after the measurements of the first week on average. These second measurements were not used for the model development. We used two data sources as exposure predictors: 1) a questionnaire on potentially exposure relevant characteristics and behaviors and 2) modeled RF-EMF from fixed site transmitters (mobile phone base stations, broadcast transmitters) at the participants' place of residence using a geospatial propagation model. Relevant exposure predictors, which were identified by means of multiple regression analysis, were the modeled RF-EMF at the participants' home from the propagation model, housing characteristics, ownership of communication devices (wireless LAN, mobile and cordless phones) and behavioral aspects such as amount of time spent in public transports. The proportion of variance explained (R^2) by the final model was 0.52. The analysis of the agreement between calculated and measured RF-EMF showed a sensitivity of 0.56 and a specificity of 0.95 (cut-off: 90th percentile). In the validation study, the sensitivity and specificity of the model were 0.67 and 0.96, respectively. We could demonstrate that it is feasible to model personal RF-EMF exposure. Most importantly, our validation study suggests that the model can be used to assess average exposure over several months.

1. Introduction

In our everyday environment, radio frequency electromagnetic fields (RF-EMFs) are emitted by numerous sources such as mobile and cordless phones, broadcast transmitters or wireless LAN (W-LAN). Consequently, the distribution of RF-EMF is temporally and spatially highly variable (Frei et al., 2009), which poses a major challenge for exposure assessment in epidemiological research. In principle, two different types of exposure sources can be distinguished: sources close to the human body and sources farther away. Sources close to the body (e.g. mobile phone handsets) typically cause high and periodic short-term exposure, mainly to the head, while more distant sources (e.g. mobile phone base stations) in general cause lower but relatively continuous whole-body exposure.

So far research has mainly focused on RF-EMF exposure from mobile phone handsets. Such exposures have been assessed by questionnaires about the use of mobile phones, ideally combined with objective data from the mobile phone operators (Vrijheid et al., 2008). However, reliable exposure assessment of environmental far-field RF-EMF is more challenging. It has been shown that using a simple exposure proxy, such as the lateral distance to a mobile phone base station (Navarro et al., 2003; Santini et al., 2003; Blettner et al., 2009), is inaccurate and leads to substantial exposure misclassification (Schüz and Mann, 2000; Bornkessel et al., 2007; Neubauer et al., 2007). More sophisticated approaches used spot measurements at the homes of study participants (Hutter et al., 2006; Berg-Beckhoff et al., 2009), 24 h personal measurements (Thomas et al., 2008; Thuróczy et al., 2008; Kühnlein et al., 2009; Viel et al., 2009), measurements in different microenvironments (Joseph et al., 2008) or modeling of

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mobile phone base station or broadcast transmitter radiation (Ha et al., 2007; Neitzke et al., 2007; Breckenkamp et al., 2008). However, it is still unclear to what extent these approaches reflect long-term personal exposure from all RF-EMF.

In the QUALIFEX study (health related quality of life and radio frequency electromagnetic field exposure: prospective cohort study), we want to investigate the health effects of RF-EMF exposure in a study population of 1400 participants. The use of personal exposure meters (exposimeters) would be appealing but would require a lot of organizational effort in such a large collective thus making the study very expensive. In addition, the handling of such devices is a demanding and time-consuming task for the study participants, which would likely introduce a participation bias. The simultaneous collection of measurements and self-reported health related quality of life is critical because study participants are aware of the study purpose and the answers about their health status might be biased by their perceived exposure, or they might even manipulate the measurements by placing the exposimeter at positions where high RF-EMF exposures are expected thus yielding unreliable results. The purpose of this study was to develop and validate a statistical RF-EMF exposure prediction model which is suitable for the QUALIFEX study. For the development of the exposure prediction model we used measurements over one week of 166 volunteers carrying a personal exposimeter (Frei et al., 2009), combined with information from questionnaires as well as modeled RF-EMF from fixed site transmitters (Bürgi et al., 2008; Bürgi et al., in press) at the homes of the volunteers.

2. Methods

2.1. Data collection: RF-EMF measurements and questionnaire

By the use of the personal exposimeter EME Spy 120 (SATIMO, Courtaboeuf, France, http://www.satimo.fr/), we collected RF-EMF measurements of 166 volunteers living in the city of Basel (Switzerland) and surroundings. A detailed description of the study methods is given in Frei et al. (2009). In brief, the study participants carried an exposimeter during one week and filled in an activity diary where they recorded place of stay and use of cordless and mobile phones. In order to maximize the range of exposure levels, we recruited 34 volunteers who were expected to be highly exposed at home from mobile phone base stations ($n=27$) and broadcast transmitters ($n=8$). The remaining 131 volunteers were not specifically selected. Ethical approval for the conduct of the study was received from the ethical committee of Basel on March 19th, 2007 (EK: 38/07).

The exposimeter measured exposure from twelve frequency bands every 90 s: radio FM (frequency modulation; 88–108 MHz), TV (television, 174–223 MHz and 470–830 MHz), Tetrapol (terrestrial trunked radio police; 380–400 MHz), uplink in three frequency ranges (communication from mobile phone handset to base station; 880–915, 1710–1785, 1920–1980 MHz), downlink in three frequency ranges (communication from mobile phone base station to handset; 925–960, 1805–1880, 2110–2170 MHz), DECT (digital enhanced cordless telecommunications; 1880–1900 MHz) and W-LAN (wireless local area network; 2400–2500 MHz). The median number of recorded measurements per person was 6472. A study assistant visited participants at home and handed over the exposimeter device, a personal diary and a questionnaire. The questionnaire contained questions about characteristics of the participants' homes, about their workplaces, the use of wireless devices such as mobile phone handsets or cordless phones, about behavioral aspects like the time spent in public transport per week and about socio-demographic characteristics. For each individual we calculated a weekly arithmetic mean value for each frequency band. Due to the high proportion of measurements below the detection limit, mean values were calculated using the robust regression on order statistics (ROS) method (Röösli et al., 2008). For the mean value, we only considered measurements when participants did not use their own mobile or DECT phones because of the limited capability of the exposimeters to adequately measure body-close sources (Inyang et al., 2008). Thus, the mean values represent exposure to environmental RF-EMF sources without own phone use.

2.2. Geospatial propagation model: RF-EMF from fixed site transmitters at home (S_{mod})

We developed a three-dimensional geospatial propagation model in which average RF-EMF from fixed site transmitters (mobile phone base stations and broadcast transmitters) was modeled for the study region (in- and outside of buildings) (Bürgi et al., 2008, in press). The model calculation is based on a comprehensive database of all transmitters (position, transmission direction, antenna types and radiation pattern, transmitter power and number of channels) and a three-dimensional building model of the study area, considering, for example, shielding and diffraction by buildings and topography. Indoor values were modeled using the same damping factor for all buildings. The geographical coordinates of the addresses at which the participants lived were identified by the Swiss Federal Statistical Office. In combination with the information about the floor level of the participants' apartments, mean RF-EMF in a horizontal radius of 5 m around the coordinate at home was determined for each study participant.

2.3. RF-EMF exposure model development

A multivariable regression model was developed to predict personal mean RF-EMF exposure. We developed a model for average exposure when being at home (will be referred to in the following as home model) and a model for total exposure over one week (total model). In a first step we developed the home model. By means of the diary, we identified the measurements which had been taken at the homes of the study participants. We hypothesized that the modeled mean value of fixed site transmitters at home from the geospatial model (S_{mod}) is an important predictor for exposure at home. This predictor is supposed to be modified by different housing characteristics like for example the type of the house wall (a house wall consisting of concrete, for example, is expected to damp exposure from fixed site transmitters to a larger extent than a house wall consisting of wood). Additional sources like indoor devices are also assumed to play a role regarding exposure. Based on these different physical properties of the predictor variables, we developed a non-linear model of the form

$$S = \beta_1 \times S_{\mathrm{mod}} \times e^{\beta_2 \times z_1} \times e^{\beta_3 \times z_2} \times \ldots + \beta_4 \times x_1 + \beta_5 \times x_2 + \ldots \quad (1)$$

where S represents mean RF-EMF exposure (power flux density), z_i represent housing factors (multiplicative) and x_i represents additional indoor sources. The terms z_i are exponentiated but we present back transformed coefficients in the Result section. At first we evaluated the predictive effects of all predictors on the frequency band (or combination of frequency bands) on which they are expected to have an effect due to physical considerations (for example the ownership of a W-LAN is supposed to have an impact on exposure from W-LAN radiation at home). All tested predictors are shown in Table 1. All predictor variables which showed an association with their respective frequency band(s) were then included into the home model predicting exposure to all measured frequency bands at home. We selected the final home model based on the Akaike information criterion (AIC) by stepwise eliminating predictor variables.

The variables included in the home model provided the basis for the total model. The home model was extended by taking into consideration behavioral aspects and activities of a person. Potential

Table 1
List of all predictor variables tested for the home model (bold variables) and for the total model (all variables).

Variable	Type	Description
S_{mod}	Cont.	Modeled RF-EMF from fixed site transmitters (mobile phone base station and broadcast transmitters) at the home of the participants calculated with the geospatial propagation model
Wall	Binary	House wall of the participants' home: 0 = wood or brick, 1 = concrete (housing factor)
Window frame	Binary	Window frames of the participants' home: 0 = no metal, 1 = metal (housing factor)
Glazing	Binary	Glazing of the windows of the participant's home: 0 = single glazing; 1 = double or triple glazing (housing factor)
DECT	Binary	Ownership of a DECT phone at home: 0 = no; 1 = yes
DECT bedroom	Binary	Base station of the DECT phone in the participant's bedroom: 0 = no; 1 = yes
W-LAN	Binary	Ownership of wireless LAN at home: 0 = no, 1 = yes
W-LAN bedroom	Binary	W-LAN router in the participant's bedroom: 0 = no, 1 = yes (and not switched off during nighttime)
Mobile phone	Binary	Ownership of a mobile phone: 0 = no, 1 = yes
Outdoor	Cont.	Hours per week spent outdoors
Shopping	Cont.	Hours per week spent shopping
Restaurant	Cont.	Hours per week spent in a restaurant, bar, café, disco or cafeteria
Percent FTE	Cont.	Percent full-time equivalent spent at an external workplace (other than home)
Public transport	Cont.	Hours per week spent in a train, tram or bus
Car	Cont.	Hours per week spent in a car
DECT daytime	Binary	Cordless phone at the place where the participants spend most of their time during daytime (8 am–6 pm) on workdays: 0 = no, 1 = yes

predictors were variables which specify the time spent at locations where high exposures were measured (Frei et al., 2009), like for example the time spent in public transport. The procedure to obtain the final total model was analogue to the development of the home model.

2.4. Evaluation of the home and total models

We evaluated the models by comparing the measured with the predicted values. The agreement between measured and predicted values was assessed by calculating the Spearman rank correlation coefficient as a measure of the monotone association between the continuous variables. Exposure misclassification is given by the sensitivity and specificity including their 95% confidence intervals (CIs), using the measurements as gold standard, after dichotomizing both measured and calculated exposures at their 90th percentile. The 90th percentile is a common chosen cut-off for RF-EMF exposure classification (Kühnlein et al., 2009; Schmiedel et al., 2009) because of the skewed data distribution. In addition, we wanted to evaluate the relative importance of the different predictor variables. In a first step we calculated the proportion of variance explained (R^2) by the models when only including the predictor variable S_{mod}. We then calculated the proportion of explained variance by adding the housing factors (multiplicative terms) to the model and by finally including the additive factors. Statistical analyses were carried out using STATA version 10.1 (StataCorp, College Station, TX, USA). All calculations were done with the values for the power flux density (mW/m²).

2.5. Validation study

We performed a validation study in order to investigate whether the models can be used to predict mean weekly exposure also several weeks later. We invited 32 participants to measure RF-EMF exposure during a second week. An important criterion for the selection of participants for the validation study was a motivated and reliable participation during the first week with plausible diary entries and measurements. In addition, we paid attention to include some of the highly exposed individuals in order to obtain an exposure contrast also for the validation study. The questionnaire was only filled in during the first week of measurements. We only adapted predictor variables for three persons who had experienced a major change in their exposure situation between the development and validation studies: one had moved house, so the predicted RF-EMF from the geospatial model was calculated for the new coordinate, one person had in the meantime bought a mobile phone and one a cordless phone. We then applied the exposure models to the second measurements (which had not been used for the model development) and calculated the Spearman correlation coefficient between the measured and predicted exposure and the sensitivity and specificity of the models (cut-off: 90th percentile). In the following we will use the term “development study” for the measurements of the first week and “validation study” for the measurements of the second week.

2.6. Sensitivity analysis

Model diagnostics including residual analyses revealed that the models were not accurate for three study participants, but they were influential for coefficient estimation. We supposed that the generalizability of the models in another collective would be increased if these three outliers are omitted from the final model coefficient estimation but we performed a sensitivity analysis by including these three observations into the home and total models and by examining the relative change of the model coefficients. In addition, we calculated the sensitivity and specificity of the models including these three observations.

To test the robustness of our data we performed a cross-validation for the home and total models by leaving out one observation at a time and calculating the predicted value of the omitted observation. We then calculated the sensitivity and specificity again with the cross-validated predictors.

3. Results

3.1. Characteristics of study participants

The characteristics of the study participants of the development and validation studies included in the analyses are listed in Table 2. In the development study, mean age of the study participants was 2.6 years (range: 18 to 78 years) and 92 (55.2%) participants were women. 32 volunteers participated in the validation study; thereof one measurement had to be excluded because of inappropriate handling of the exposimeter thus leaving 31 participants for analyses. The

Table 2
Characteristics of the study participants from the development and validation study included in the analysis (all participants from the validation study also took part in the development study).

	Development study		Validation study	
Sex	*n*	%	*n*	%
Male	73	44.8	9	29.0
Female	90	55.2	22	71.0
Age (years)				
18–34	62	38.0	12	38.7
35–49	48	29.5	13	41.9
50–64	40	24.5	6	19.4
>64	13	8.0	0	0.0
Ownership of wireless devices at home				
Persons owning a mobile phone handset	143	87.7	27	87.1
Persons owning a cordless phone	118	72.4	22	71.0
Persons owning W-LAN	55	33.7	9	29.0

proportion of female subjects (71.0%) was higher and the volunteers were slightly younger (mean age: 38.3 years) in the validation study, but there was no difference with respect to indoor sources at home. The development and validation studies were on average separated by 21.2 weeks (range: 3 to 41 weeks).

3.2. Model for exposure at home (home model) and total exposure (total model)

All tested variables are explained in detail in Table 1. The predictor variables are all derived from self-reports in the questionnaire except for S_{mod}. Table 3 a) and b) shows the association of all tested potential predictor variables with their corresponding frequency band(s). Based on the AIC criterion the following predictor variables were finally included into the home model: "S_{mod}", "wall", "window frame", "mobile phone", "W-LAN" and "DECT bedroom" (Table 4 a). The same variables were included into the total model together with the following additional variables: "DECT daytime", "percent FTE", "public transport" and "car" (Table 4 b). The proportion of variance explained (R^2) by the home and total models was 0.56 and 0.52, respectively. Table 4 a) and b) shows the coefficients of the predictor variables included in the final home and total models with their corresponding 95% confidence intervals and the explained variance of different (groups of) predictor variables (R^2). In the home and the total models, most of the variance is explained by the value of the propagation model.

3.3. Evaluation of the home and total models

Fig. 1 a) and b) shows a box plot of measured RF-EMF for the three categories (<50th, 50–90th, >90th percentile) of predicted RF-EMF exposures for the development study. Fig. 1 a) shows the data of the home model and Fig. 1 b) shows the data of the total model. There was a clear association between the measured and predicted exposure: for the home model, the Spearman correlation coefficient between measured and predicted exposure was 0.51 (95%-CI 0.39–0.61) and for the total model 0.51 (95%-CI 0.38–0.61). Table 5 a) shows how well three exposure categories (<50th, 50–90th, >90th percentile) are predicted by the home and total models for the development study. The sensitivity (cut-off: 90th percentile) of the home model was 0.56 and the specificity 0.96 and for the total model 0.56 and 0.95, respectively.

3.4. Validation study

In the validation study, the Spearman correlation coefficient between measured and predicted exposure for the home model was 0.65 (95%-CI 0.38–0.81). The sensitivity of the home model was 0.67 and the specificity 0.96. In the total model, the Spearman correlation coefficient was 0.75 (95%-CI 0.53–0.87). As in the home model, the sensitivity of the total model was 0.67 and the specificity 0.96. Table 5 b) shows how well the three exposure categories (<50th, 50–90th, >90th percentile) are predicted by the two models.

Table 3

Multivariable regression coefficients of potential additive and multiplicative predictor variables for mean exposure of different frequency bands at home (a) and for mean exposure over one week (b).

a)

Predictor variable	Measured frequency band			
	Fixed site transmitters[a] (95%-CI)	Uplink (95%-CI)	W-LAN (95%-CI)	DECT (95%-CI)
S_{mod}	0.433 (0.005, 0.861)			
Wall (housing factor)[b]	0.394 (0.208, 0.748)			
Window frame (hous. factor)[b]	0.563 (0.314, 1.009)			
Glazing (housing factor)[b]	0.780 (0.291, 2.090)			
Mobile phone[c]		0.012 (0.008, 0.017)		
W-LAN[c]			0.009 (0.006, 0.012)	
W-LAN bedroom[c]			0.000 (−0.013, 0.013)	
DECT[c]				0.033 (0.023, 0.044)
DECT bedroom[c]				0.000 (−0.029, 0.028)

b)

Predictor variable	Measured frequency band			
	Fixed site transmitters[a] (95%-CI)	Uplink (95%-CI)	W-LAN (95%-CI)	DECT (95%-CI)
S_{mod}	0.231 (0.190, 0.272)			
Wall (housing factor)[b]	0.606 (0.377, 0.975)			
Window frame (hous. factor)[b]	0.392 (0.187, 0.819)			
Mobile phone[c]		0.008 (−0.007, 0.023)		
W-LAN[c]			0.007 (0.001, 0.013)	
DECT bedroom[c]				0.007 (−0.013, 0.028)
DECT daytime[c]				0.025 (0.012, 0.038)
Outdoor[c,d]	0.006 (−0.009, 0.022)			
Shopping[c,d]	0.011 (−0.061, 0.084)	0.005 (−0.034, 0.045)	0.006 (−0.010, 0.021)	0.024 (−0.014, 0.062)
Restaurant[c,d]	−0.015 (−0.059, 0.029)	0.001 (−0.024, 0.027)	−0.002 (−0.014, 0.010)	0.008 (−0.017, 0.033)
Percent FTE[c,e]	0.003 (0.000, 0.006)	0.003 (0.001, 0.004)	0.000 (0.000, 0.001)	0.001 (0.000, 0.003)
Public transport[c,d]	0.015 (−0.015, 0.045)	0.027 (0.010, 0.044)		
Car[c,d]	0.000 (−0.004, 0.005)	0.037 (0.012, 0.062)		

Separate multivariable models were fitted for the different frequency bands. The variables are explained in more detail in Table 1.

[a] Fixed site transmitters include FM radio broadcast, TV broadcast, Tetrapol and mobile phone base stations.

[b] Multiplicative factors (back transformed). The factors are therefore statistically significant if the 95% confidence interval does not include 1; *For example, for the multiplicative housing factors* (Table 3 a): An increase of 1 mW/m^2 in the geospatial propagation model (S_{mod}) leads to an increase of 0.433 mW/m^2 (95%-CI 0.005 to 0.861) of exposure from fixed site transmitters (first column). If a wall consists of concrete ("wall"), exposure from fixed site transmitters has to be multiplied by 0.394. Accordingly, for a window frame containing metal ("window frame") a factor of 0.563 has to be multiplied and for a double or triple glazed window ("glazing") a factor of 0.780.

[c] Additive factors (statistically significant if the 95% confidence interval does not include 0): *For example, for an additive factor* (Table 3 a): "DECT" (ownership of a cordless phone at home) increases DECT radiation at home by 0.033 mW/m^2 (last column).

[d] Regression coefficient for 10 h.

[e] Regression coefficient for 10**%** increase.

Table 4
Regression coefficients (β) and 95% confidence intervals (CI) of the variables predicting exposure from all measured frequency bands in the (a) home model and (b) total model.

a)

Variable	Coefficient (β)	(95%-CI)	Cumulative R^2
Modeled RF-EMF at home			0.34
S_{mod}	0.396	(0.339 to 0.452)	
Housing factors[a]			0.52
Wall	0.346	(0.193 to 0.623)	
Window frame	0.476	(0.253 to 0.895)	
Additive factors			0.56
Mobile phone	0.038	(0.016 to 0.060)	
W-LAN	0.045	(0.012 to 0.078)	
DECT bedroom	0.046	(−0.005 to 0.098)	

b)

Variable	Coefficient (β)	(95%-CI)	Cumulative R^2
Modeled RF-EMF at home			0.25
S_{mod}	0.258	(0.210 to 0.306)	
Housing factors[a]			0.40
Wall	0.460	(0.244 to 0.864)	
Window frame	0.327	(0.117 to 0.917)	
Additive factors			0.52
Mobile phone	0.023	(−0.007 to 0.054)	
W-LAN	0.030	(0.003 to 0.057)	
DECT bedroom	0.024	(−0.019 to 0.066)	
DECT daytime	0.038	(0.011 to 0.066)	
Percent FTE[b]	0.006	(0.002 to 0.009)	
Public transport[c]	0.039	(0.004 to 0.073)	
Car[c]	0.040	(−0.011 to 0.091)	

The coefficients can be applied in Eq. (1) to predict mean exposure of a person with specific characteristics.
[a] The coefficients of the housing factors are back transformed (exponentiated); *For example* (Table 4 a): a person with a modeled value at home from fixed site transmitters (S_{mod}) of 0.15 mW/m^2 whose house wall consists of concrete and the window frames are made of plastic, owning a mobile phone but no W-LAN and no cordless phone in the bedroom, has a mean exposure level (S) at home of $S = (0.396 \times 0.15) \times 0.346^1 \times 0.476^0 + (0.038 \times 1) + (0.045 \times 0) + (0.046 \times 0) = 0.059$ (unit: mW/m^2).
[b] Coefficient for 10% increase.
[c] Coefficient for 10 h.

3.5. Sensitivity analysis

We recalculated the coefficients of the home and total models after including the three influential observations which were previously excluded. In the home model, the deviations of the coefficients from the original coefficients varied between 0.6% (S_{mod}) and 40.9% ("mobile phone"). The sensitivity and specificity of the home model were 0.50 and 0.95, respectively, and the Spearman correlation coefficient between measured and predicted exposure was 0.50 (95%-CI: 0.37–0.60). In the total model the deviation from the original coefficients ranged from 2.1% ("window frame") to 128.5% ("DECT bedroom"). The sensitivity and specificity of the total model were 0.63 and 0.96, respectively, and the Spearman correlation coefficient 0.47 (95%-CI: 0.35–0.58).

The sensitivity and specificity of the home and total models after applying the cross-validation technique were similar to the sensitivity and specificity of the models of the development study. For the home model, sensitivity and specificity were 0.50 and 0.95, respectively, and for the total model 0.56 and 0.95, respectively. The Spearman correlation coefficient between the predicted values by the cross-validation and the measured values was 0.43 (95%-CI: 0.30–0.55) for the home model and 0.44 (95%-CI: 0.31–0.56) for the total model.

4. Discussion

We developed non-linear regression models for the prediction of personal total RF-EMF exposure levels and exposure at home from a combination of personal exposure measurements, questionnaire data and modeling of RF-EMF from fixed site transmitters. The R^2 of the home model was 0.52 and of the total model 0.56. In the validation study we could demonstrate that the models are also applicable to the measurements of the second week, which had been taken on average 21 weeks later and were not used for the model development.

4.1. Strengths

To our knowledge, this is the first study to collect data on RF-EMF exposure on such a comprehensive level. We used a longer measurement period than previous personal exposure measurement studies (Thomas et al., 2008; Thuróczy et al., 2008; Kühnlein et al., 2009; Viel et al., 2009). Our geospatial propagation model, which we developed for the whole study region, allowed the prediction of exposure from fixed site transmitters at the homes of the study participants. This approach has also been used in previous studies (Ha et al., 2007; Neitzke et al., 2007; Breckenkamp et al., 2008), but were not compared with personal exposure measurements as we did. In summary, this is the first study that combines modeled RF-EMF exposure with personal exposure relevant characteristics and behavior to estimate personal exposure.

This extensive data collection allowed us to build empirical models based on physical laws. There could be numerous potential predictors for RF-EMF exposure. In order to reduce false positive associations and to obtain generalizable and robust models, only predictors which have a physically interpretable effect on RF-EMF exposure were tested. We put a lot of emphasis on testing the robustness of the models and to validate them. The validation study demonstrated that the models are able to predict the independent data of a second measurement campaign. This suggests that predicted exposure represents average exposure over several months.

4.2. Limitations

The models are based on a relatively small number of observations (163 study participants). Some model coefficients changed by more than 50**%** when including the three influential observations, which demonstrates that the study sample plays an important role. However, all predictors are physically plausible and the change of their coefficients had a negligible effect on the sensitivity and specificity of the models. Also the results of the cross-validation showed that the models are quite robust. The validation study was small and with the same participants, but showed an acceptable reliability, although a validation in an independent sample is still missing. The application of the models in other settings (for example other countries) or in the future needs a recalibration of the model coefficients and other potentially relevant factors have to be evaluated.

The exposure prediction models predict environmental exposure only and do not take into account body-close sources such as mobile or cordless phones. It has been argued that exposure to environmental fields is not relevant in comparison to exposure from a mobile phone. With respect to exposure at the head, exposure resulting from an operating mobile phone is considerably higher compared to a typical everyday exposure from a mobile phone base station (Neubauer et al., 2007). Regarding whole-body exposure, however, the situation is not yet as conclusive. According to a rough dosimetric estimation, 24 h exposure from a base station (1–2 V/m) corresponds to about 30 min of mobile phone use (Neubauer et al., 2007). We are aware that for the investigation of health effects of RF-EMF exposure, the use of cordless and mobile phones should not be neglected. In this case we suggest using both the modeled environmental RF-EMF exposure from the exposure prediction model as well as the use of cordless and mobile phones as independent exposure variables in a multivariable regression model.

The sensitivity of our exposure models (0.56 for the home and total models) seems to be relatively low in comparison to the high

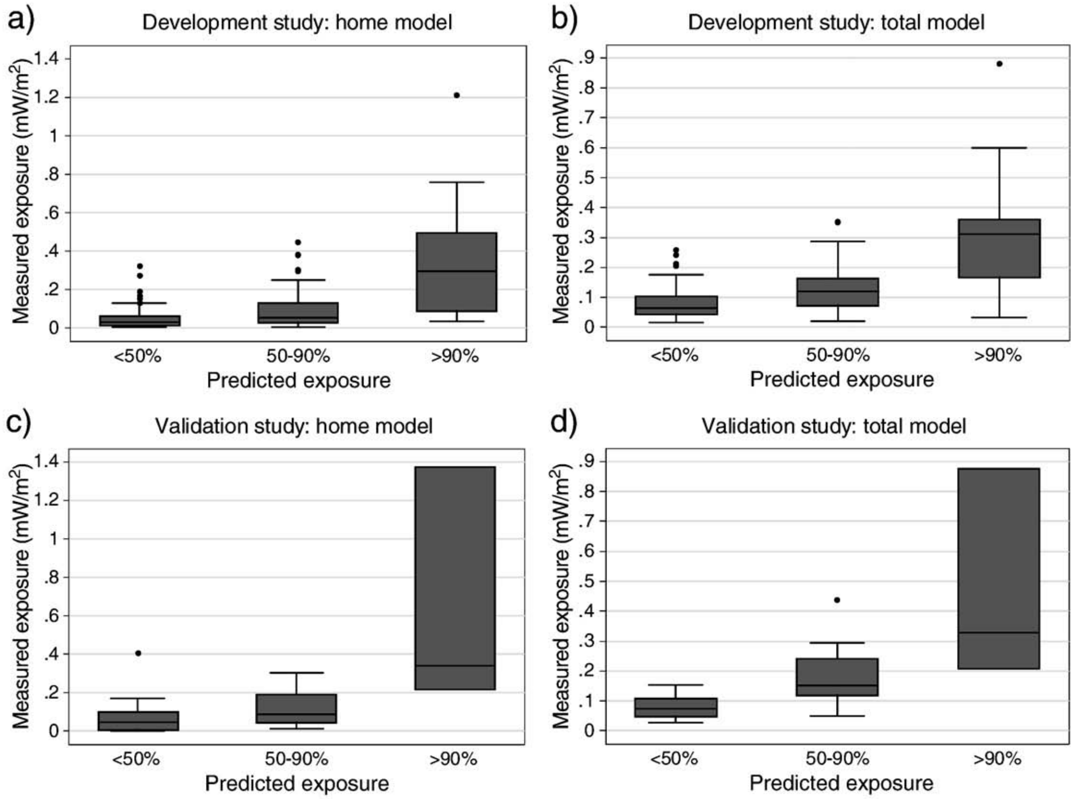

Fig. 1. Boxplots showing the distribution of measurements for three categories of predicted values (<50th, 50–90th, >90th percentile) for the development study (a) and b)) and the validation study (c) and d)). The horizontal lines mark median values, the inner boxes the 25–75% quantiles and the lines the lower and upper adjacent values (furthest observation which is within one and a half interquartile range of the lower/upper end of the box).

specificity (0.96 for the home model and 0.95 for the total model). For the assessment of health effects due to RF-EMF exposure, a high specificity is much more important than a high sensitivity because the exposure distribution is skewed and the proportion of highly exposed individuals is small (Neubauer et al., 2007). For this reason we chose the 90th percentile as cut-off for highly exposed. Low sensitivity implies that a part of the few highly exposed individuals are erroneously pooled together with the large group of lowly exposed individuals, resulting in only a small dilution of this large group. Reversely, a high specificity implies that only a few of the many lowly exposed individuals are erroneously classified as highly exposed. Thus, the exposed group is not heavily diluted with unexposed individuals.

Table 5
Comparison of three categories (<50th, 50–90th, >90th percentile) of predicted exposure with measured exposure in the development (a) and validation (b) studies for the home and total models.

a)				
Development study ($N=163$)		Measurements		
	mW/m^2	<50%	50–90%	>90%
Home model	<50%	52	29	2
	50–90%	28	32	5
	>90%	2	4	9
Total model	<50%	54	28	0
	50–90%	26	32	7
	>90%	2	5	9
b)				
Validation study ($N=31$)		Measurements		
	mW/m^2	<50%	50–90%	>90%
Home model	<50%	11	4	1
	50–90%	5	7	0
	>90%	0	1	2
Total model	<50%	13	3	0
	50–90%	3	8	1
	>90%	0	1	2

For example in the home model, 83 persons were predicted to be in the category <50%. Of these persons, 52 were also measured to be in that category, 29 were measured to be in the adjacent category (50–90%) and 2 were measured to be in the highest exposure group (>90%). A perfect model would have all values at the diagonal positions and none at all off-diagonal positions.

4.3. Interpretation

Except for the modeled exposure from fixed site transmitters (S_{mod}) at home (geospatial propagation model), the predictor variables are derived from questionnaire data. This implies that exposure can be assessed without the need for an extensive measurement campaign using personal exposimeters.

Our exposure prediction models suggest that the modeled exposure S_{mod} is an essential predictor because it explains a considerable part of the variance. Since people normally spend a considerable part of their time at home, it is crucial to be able to precisely define exposure at the home of a study participant. We therefore think that it is essential to have such a geospatial model for the study region. In our opinion, RF-EMF exposure assessment just based on questionnaire data would be hard to achieve and is vulnerable to reporting bias in combination with health questions; for example, diseased persons might overestimate their exposure (Vrijheid et al., 2008). On the contrary, we are convinced that bias does not play a major role in our exposure prediction models although self-reported components are included. Firstly, a high proportion of the variance explained by the prediction models is due to the propagation model, which cannot be biased. Basic statements about the ownership of a W-LAN, cordless or mobile phone are unlikely to be heavily biased. The other variables in our exposure models (type of wall, window frame, percent FTE and time spent in cars and public transport) are unlikely to be related to RF-EMF exposure by lay persons.

An assessment of exposure from fixed site transmitters at the workplace of the study participants by means of the geospatial propagation model would probably improve the exposure prediction model for total exposure. Business buildings, however, are usually quite big and therefore information about the exact location of the workplace would be needed because of the variation of RF-EMF exposure at a small scale. It would not be feasible to obtain this information by means of a questionnaire. Furthermore, if persons are selected by residency in a certain city, the propagation model would have to be extended to a bigger area because some persons might not work in the respective study area.

In a next step, the presented models will be applied to predict mean RF-EMF exposure in a study population of 1400 study participants to investigate a potential association between health related quality of life and RF-EMF exposure.

To conclude, our study demonstrates that it is feasible to model personal RF-EMF exposure in our study area by means of a geospatial propagation model and a questionnaire which contains the most important questions regarding RF-EMF exposure. This implies that environmental RF-EMF exposure can be assessed without the need for extensive measurement campaigns. The validation study showed that RF-EMF exposure can be predicted for a longer time period, which allows investigating health effects of exposure over several months.

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Article 6: Classification of personal exposure to radio frequency electromagnetic fields (RF-EMF) for epidemiological research: evaluation of different exposure assessment methods

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Classification of personal exposure to radio frequency electromagnetic fields (RF-EMF) for epidemiological research: Evaluation of different exposure assessment methods

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A B S T R A C T

The use of personal exposure meters (exposimeters) has been recommended for measuring personal exposure to radio frequency electromagnetic fields (RF-EMF) from environmental far-field sources in everyday life. However, it is unclear to what extent exposimeter readings are affected by measurements taken when personal mobile and cordless phones are used. In addition, the use of exposimeters in large epidemiological studies is limited due to high costs and large effort for study participants. In the current analysis we aimed to investigate the impact of personal phone use on exposimeter readings and to evaluate different exposure assessment methods potentially useful in epidemiological studies. We collected personal exposimeter measurements during one week and diary data from 166 study participants. Moreover, we collected spot measurements in the participants' bedrooms and data on self-estimated exposure, assessed residential exposure to fixed site transmitters by calculating the geo-coded distance and mean RF-EMF from a geospatial propagation model, and developed an exposure prediction model based on the propagation model and exposure relevant behavior. The mean personal exposure was 0.13 mW/m^2, when measurements during personal phone calls were excluded and 0.15 mW/m^2, when such measurements were included. The Spearman correlation with personal exposure (without personal phone calls) was 0.42 (95%-CI: 0.29 to 0.55) for the spot measurements, −0.03 (95%-CI: −0.18 to 0.12) for the geo-coded distance, 0.28 (95%-CI: 0.14 to 0.42) for the geospatial propagation model, 0.50 (95%-CI: 0.37 to 0.61) for the full exposure prediction model and 0.06 (95%-CI: −0.10 to 0.21) for self-estimated exposure. In conclusion, personal exposure measured with exposimeters correlated best with the full exposure prediction model and spot measurements. Self-estimated exposure and geo-coded distance turned out to be poor surrogates for personal exposure.

1. Introduction

Exposure to radio frequency electromagnetic fields (RF-EMF) in everyday life is highly temporally and spatially variable due to various emitting sources like broadcast transmitters or wireless local area networks (W-LAN). The use of personal exposure meters (exposimeters) has been recommended in order to characterize personal exposure to RF-EMFs (Neubauer et al., 2007). Several exposure assessment studies have been conducted so far using exposimeters (Joseph et al., 2008; Kühnlein et al., 2009; Thomas et al., 2008; Thuróczy et al., 2008; Viel et al., 2009), which allow capture of exposure from all relevant RF-EMF sources in the different environments where a study participant spends time (Neubauer et al., 2007; Radon et al., 2006). They are suitable for measuring RF-EMF from environmental far-field sources like mobile phone base stations, but are less apt to accurately measure exposure to personal mobile or cordless phones (Inyang et al., 2008) because measurements during personal phone calls are dependent on the distance between the emitting device and the exposimeter. It is therefore expected that mean values obtained with exposimeter measurements are influenced by the personal phone use of the study participants, which is not desirable when using exposimeters for measuring environmental

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RF-EMF exposure. However, the extent to which exposimeter measurements are affected by RF-EMF sources close to the body is unknown. Other methods have been proposed for estimating RF-EMF exposure from sources operating close to the body, such as self-reported use of cordless and mobile phones or operator data (Vrijheid et al., 2009).

The use of personal exposimeters for measuring RF-EMF exposure may be considered impractical for large epidemiological studies, which require large organizational effort and resources. The handling of exposimeters is a demanding and time-consuming task for the study participants, which would likely deter many of them from participating, thus possibly introducing participation bias. Study participants might even manipulate the measurements by placing the exposimeter at positions where high RF-EMF exposures are expected, which would yield unreliable results. Moreover, exposimeters are not feasible for collecting information on long-term exposure, i.e. over several years, or on past exposure. Previous epidemiological studies have utilized other methods to estimate RF-EMF exposure which include spot measurements in bedrooms (Berg-Beckhoff et al., 2009; Hutter et al., 2006; Tomitsch et al., 2010), self-reported (Navarro et al., 2003; Santini et al., 2003) or geo-coded distance of the residence to the closest mobile phone base station (Blettner et al., 2009), and geospatial modeling of broadcast transmitters or mobile phone base stations (Bürgi et al., 2008, 2010; Ha et al., 2007; Neitzke et al., 2007). However, it is unclear how well these methods represent personal exposure to all relevant sources of RF-EMF in everyday life.

This paper summarizes comprehensive RF-EMF exposure data collected from 166 participants in the QUALIFEX study, a prospective cohort study examining exposure to radio frequency electromagnetic field exposure and health related quality of life. The aims of this study were to determine the impact of personal mobile phone use on personal RF-EMF measurements and to evaluate how reliably different exposure assessment methods could represent personal exposure.

2. Methods

2.1. Personal measurements with exposimeters

A detailed description of the recruitment of the participants and measurement protocols is summarized previously in Frei et al. (2009b). In brief, RF-EMF measurements were collected from 166 volunteers living in the city of Basel (Switzerland) and its surroundings between April 2007 and February 2008. RF-EMF exposure was measured using the personal exposimeter EME Spy 120 (SATIMO, Courtaboeuf, France, http://www.satimo.fr/). The study participants carried an exposimeter during one week and completed a time activity diary, specifically recording place of stay and detailed use of cordless and mobile phones. In addition, each participant completed a questionnaire regarding exposure relevant factors and characteristics. In order to maximize the range of exposure levels, 35 volunteers that were expected to have a high residential exposure to mobile phone base stations ($n=27$) or broadcast transmitters ($n=8$) were recruited. The remaining 131 volunteers were not specifically selected. Ethical approval for the conduct of the study was received from the ethical committee of Basel on March 19th, 2007 (EK: 38/07).

The exposimeter measured exposure from twelve frequency bands every 90 s: radio FM (frequency modulation; 88–108 MHz), TV (television, 174–223 MHz and 470–830 MHz), Tetrapol (terrestrial trunked radio police; 380–400 MHz), uplink in three frequency ranges (communication from mobile phone handset to base station; 880–915, 1710–1785, and 1920–1980 MHz), downlink in three frequency ranges (communication from mobile phone base station to handset; 925–960, 1805–1880, and 2110–2170 MHz), DECT (digital enhanced cordless telecommunications; 1880–1900 MHz) and W-LAN (wireless local area network; 2400–2500 MHz). The median number of recorded measurements per person was 6472. For each individual, a weekly arithmetic mean value was calculated for each frequency band using the robust regression on order statistics (ROS) method allowing for measurements below the detection limit of 0.0067 mW/m^2 (Röösli et al., 2008). Exposure to all measured frequency bands was derived by summing up the values of all frequency bands. Measurements that occurred during use of personal mobile or cordless phones, identified by means of the personal diary, were omitted from the calculation of mean values. To evaluate the impact of personal mobile and cordless phone use on mean values, the calculation of the mean was also derived from values of all measurements. From this point forward, these mean values are referred to as mean values without and with personal phone use.

2.2. Spot measurements in bedroom

Spot measurements were performed in the bedrooms of 134 study participants using a NARDA SRM-3000 radiation meter. Spot measurements were not performed for the remaining 32 participants due to technical and organizational difficulties. The NARDA device measured the same frequency bands as the exposimeter (Table 1). The measurements were taken as temporal averages with the root-mean-square-mode of the radiation meter. We measured 7 points per room, with the first three points in the centre of the bedroom at 1.1 m, 1.5 m and 1.7 m above the floor. Four additional points were arranged in a rectangle, each at 1 m from the centre towards a corner of the room, 1.5 m above ground.

Table 1
Description of the different exposure assessment methods.

Exposure assessment method	Unit	Description	Exposure sources[a]
Pers. measurements without personal phone use	mW/m^2	EME Spy 120 measurements every 90 s during one week without personal phone use	FM, TV, Tetrapol, Uplink, Downlink, DECT, W-LAN
Pers. measurements with personal phone use	mW/m^2	EME Spy 120 measurements every 90 s during one week including all measurements	FM, TV, Tetrapol, Uplink, Downlink, DECT, W-LAN
Spot measurements	mW/m^2	7-Point-average NARDA SRM-3000 spot measurements in bedroom	FM, TV, Tetrapol, Uplink, Downlink, DECT, W-LAN
Geo-coded distance	m	Geo-coded distance to the closest fixed site transmitter (ERP>15 W)[b]	FM, TV, Tetrapol, Downlink
Geospatial propagation model	mW/m^2	Three-dimensional model (in- and outside buildings) for fixed site transmitters	FM, TV, Tetrapol, Downlink
Full exposure prediction model	mW/m^2	Prediction model based on geospatial propagation model and exposure relevant behavior	FM, TV, Tetrapol, Uplink, Downlink, DECT, W-LAN
Self-estimated exposure	Category	Self-reported exposure in comparison to the Swiss population	FM, TV, Uplink, Downlink, DECT, W-LAN

[a]Frequency bands considered by the exposure methods: FM = FM radio broadcast transmitter; TV = Television broadcast transmitter; Tetrapol = Mobile communication system for closed groups; Uplink = Transmission from mobile phone handset to base station; Downlink = Transmission from mobile phone base station to handset; DECT = cordless phone; W-LAN = Wireless LAN.
[b]ERP = effective radiated power.

2.3. Geo-coded distance to the closest fixed transmitter

The geographical coordinates of the participants' residencies were identified by the Swiss Federal Statistical Office, and the horizontal distance of the residence to the closest fixed site transmitter (mobile phone base station or broadcast transmitter) was calculated for each study participant. To exclude microcells, only transmitters with an effective radiated power of more than 15 W were considered. Geo-coded distance was not calculated for one person who lived across the Swiss border.

2.4. Geospatial propagation model

We used a three-dimensional geospatial propagation model for the study area in which RF-EMF from fixed site transmitters (frequency bands are shown in Table 1) was modeled (in- and outside of buildings) (Bürgi et al., 2008, 2010). The model calculation was based on a comprehensive database of all transmitters (position, transmission direction, antenna types and radiation pattern, transmitter power and number of channels) and a three-dimensional building model of the study area, considering shielding and diffraction by buildings and topography. Using the geographical coordinates of the participants' residencies and the information about the floor level of the participants' apartments, mean RF-EMF in a horizontal radius of 5 m around the coordinate at home was determined for each study participant, with exception for two participants who lived outside of the area covered by the model.

2.5. Full exposure prediction model

A prediction model for personal RF-EMF exposure measured by the exposimeters was developed based on the exposure questionnaire and the modeled RF-EMF from the geospatial propagation model at the participants' residencies. The procedure for the model development and validation is summarized in detail in Frei et al. (2009a). Briefly, we identified the following relevant exposure predictors using multiple regression models: the modeled RF-EMF at the participants' home from the geospatial propagation model, modified by the type of house wall and type of window frames. Additionally, the ownership of communication devices (W-LAN, mobile and cordless phones) and behavioral characteristics (amount of time spent in public transport vehicles or cars, percent full-time equivalent) were included into the model. For the two study participants for whom the value of the geospatial propagation model was missing the measured RF-EMF was used.

2.6. Self-estimated exposure

In the exposure questionnaire, participants were asked about self-estimated exposure in comparison to the general Swiss population (separately for the sources radio FM/TV broadcast, mobile phone base stations and handsets, cordless phones and W-LAN as well as for all of these sources combined). The participants had to rate whether they considered themselves to be less, equally or more exposed compared to the average Swiss population. As nine study participants did not respond to this question, we obtained data on self-estimated exposure from 157 study participants.

2.7. Statistical analyses

Statistical analyses were carried out using STATA version 10.1 (StataCorp, College Station, TX, USA) and R version 2.9.1. All calculations were performed with the values for the power flux density (mW/m^2). Spearman rank correlations (r_s) were estimated between the values obtained using the different exposure assessment methods and the personal measurements and between the mean values of the different exposure sources (derived from the exposimeter measurements). We applied linear regression models to quantify the impact of personal mobile and cordless phone use on mean values obtained from the exposimeter measurements.

3. Results

3.1. Study participants

The characteristics of the study participants are shown in Table 2. The mean age was 42.6 years and 92 of the participants (55%) were women. The majority of the study participants owned mobile and cordless phones (88% and 72%, respectively) and approximately one third owned a W-LAN at home. The average lengths of mobile and cordless phone use per week recorded in the personal diaries were 17 and 42 min, respectively.

3.2. Contribution of personal mobile and cordless phone use to individual RF-EMF exposure

Fig. 1(a) shows scatter plots of the association between mobile phone use and mean values of all 3 uplink bands combined with (solid slopes) and without (dashed slopes) personal phone calls and Fig. 1(b) shows the corresponding data for the cordless phone use. Mean personal exposure to uplink (with personal phone use) increased by 0.038 mW/m^2 (95%-CI: 0.022 to 0.054 mW/m^2; intercept: 0.034 mW/m^2) per hour of mobile phone use and exposure to DECT cordless phones by 0.023 mW/m^2 (95%-CI: 0.012 to 0.033 mW/m^2; intercept: 0.026 mW/m^2) per hour of cordless phone use. Exposure over all frequency bands (total exposure; data not shown) increased by 0.026 mW/m^2 (95%-CI: −0.025 to 0.077 mW/m^2) per hour of mobile phone use and by 0.027 mW/m^2 (95%-CI: 0.009 to 0.046 mW/m^2) per hour of cordless phone use. In case of mobile phone use without personal phone use, exposure to uplink increased by 0.023 mW/m^2 (95%-CI: 0.007 to 0.038 mW/m^2) per hour of mobile phone use (Fig. 1(a)). The corresponding increase in the DECT band was 0.009 mW/m^2 (−0.001 to 0.018 mW/m^2) per hour of cordless phone use (Fig. 1(b)). Total exposure calculated without personal phone use increased by 0.010 mW/m^2 (95%-CI: −0.039 to 0.058 mW/m^2) per hour of mobile phone use and by 0.013 mW/m^2 (95%-CI: −0.005 to 0.031 mW/m^2) per hour of cordless phone use.

Fig. 2 shows the mean values and contributions of the different sources with (Fig. 2(a)) and without (Fig. 2(b)) personal phone use. The mean values over all frequency bands were 0.15 mW/m^2 with personal phone use compared to 0.13 mW/m^2 without personal phone use and this difference is statistically significant (t-test, $p<0.001$). The increase of 12.4%, when including measurements during personal phone use, was mainly influenced by the use of cordless phones (64.2%). The contribution of the uplink band to total exposure was 29.8% with personal phone use. Without personal phone use the contribution of uplink was 29.1%. Exposure to DECT phones contributed 27.8% to total exposure when measurements during personal cordless phone calls were included and 22.7% when such measurements were excluded. The Spearman correlation between the mean values with and without personal phone use was 0.94 (95%-CI: 0.92 to 0.96) (Table 3).

3.3. Exposure assessment methods: characteristics and correlations

Fig. 3(a) to (e) shows box plots of the personal measurements over all frequency bands (without personal phone use) for three categories of the alternative exposure assessment methods and the corresponding Spearman correlation coefficients. Table 3

Table 2
Characteristics of the study participants.

	n	%
Sex		
Male	74	44.6
Female	92	55.4
Age (years)		
18–34	62	37.4
35–49	50	30.1
50–64	41	24.7
>64	13	7.8
Ownership of wireless devices at home		
Persons owning a mobile phone handset	143	87.7
Persons owning a cordless phone	118	72.4
Persons owning W-LAN	55	33.7
Use of mobile phone		
No use	65	39.2
1 min–1 h	86	53.0
>1 h	13	7.8
Use of cordless phone		
No use	61	36.8
1 min–1 h	66	40.9
>1 h	36	22.3

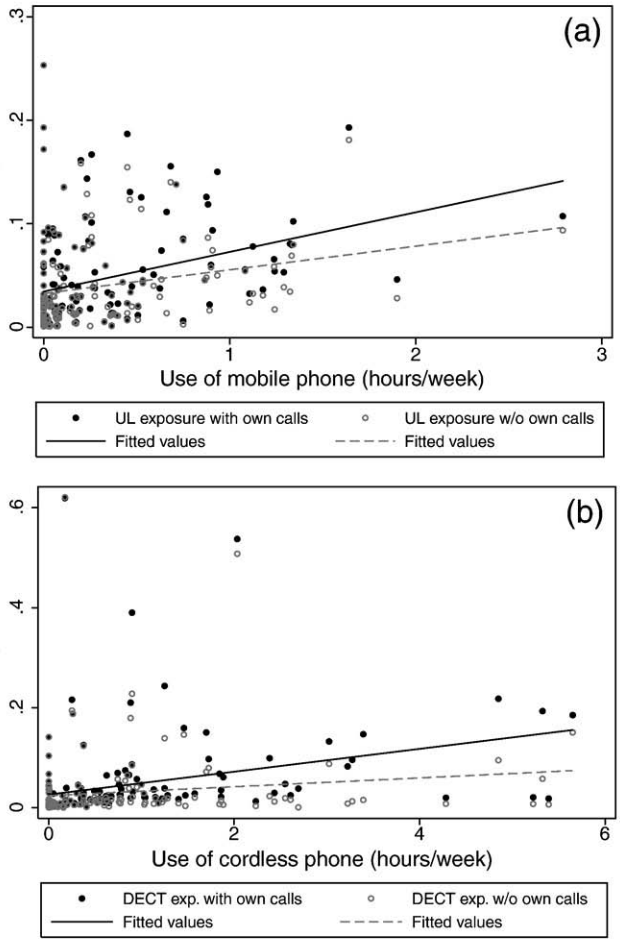

Fig. 1. Scatter plots and linear fits of mobile (a) phone use and mean exposure to uplink (UL) and cordless (b) phone use and mean exposure to DECT radiation obtained from the personal measurements. The black points represent mean values when personal mobile phone calls were included and the grey circles when such values were excluded. The solid and dashed slopes represent the linear regression line for the mean values with and without personal phone use, respectively. Note that the scale for the *x* and *y* axes are doubled in (b) compared to (a). Therefore, the slopes of the two figures can directly be compared.

shows the characteristics of the different exposure assessment methods as well as the 95% confidence intervals of the Spearman correlation coefficients. The mean values derived from the personal measurements (with and without personal phone use), from the spot

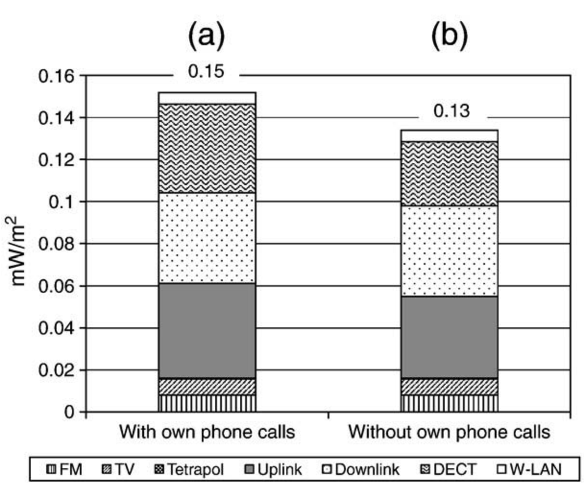

Fig. 2. Mean exposure over one week and contributions from the different sources including (a) and omitting (b) measurements during personal mobile and cordless phone use from the calculation.

Table 3
Characteristics of the different exposure assessment methods and Spearman correlations with the personal measurements (without personal phone use).

Exposure assessment method	*n*	Mean	Min	Max	Correlation (Spearman)	95%-CI
Personal measurements without personal phone use	166	0.13	0.01	0.88	1	(–)
Personal measurements with personal phone use	166	0.15	0.02	0.89	0.94	(0.92; 0.96)
Spot measurements	134	0.11	0.00	3.53	0.42	(0.27; 0.55)
Geo-coded distance	165	208	4	1026	−0.03	(−0.18; 0.12)
Geospatial propagation model	164	0.14	0.00	2.01	0.28	(0.14; 0.42)
Full exposure prediction model	166	0.12	0.03	0.55	0.50	(0.37; 0.61)
		Equal[a]	Lower[a]	Higher[a]		
Self-estimated exposure	157	102 (65%)	37 (24%)	18 (11%)	0.06	(−0.10; 0.21)

[a] In comparison to the general Swiss population.

measurements, and the geospatial propagation and the full exposure prediction model were very similar (Table 3). The exposure range was smallest for the full exposure prediction model (between 0.03 and 0.55 mW/m^2) and largest for the spot measurements in the bedrooms of the study participants (between 0.00 and 3.53 mW/m^2). The average distance of the study participants' residences to the closest transmitter was 208 m. The majority of the study participants (65%) considered themselves to be equally exposed to RF-EMF compared to the average Swiss population.

The spot measurements, geospatial propagation model and full exposure prediction model were observed to be associated with the personal measurements without personal phone use (Fig. 3(a), (c) and (d), respectively), and the corresponding Spearman correlation coefficients were 0.42 (95%-CI: 0.27 to 0.55), 0.28 (95%-CI: 0.14 to 0.42), and 0.50 (95%-CI: 0.37 to 0.61), respectively. No associations were observed between personal exposimeter measurements and either the geo-coded distance to the closest fixed site transmitter or self-estimated exposure (Fig. 3(b) and (e), respectively). The lack of association was reflected in a low Spearman rank correlation (Table 3) for geo-coded distance ($r_s = -0.03$ (95%-CI: −0.18 to 0.12) and for self-estimated exposure ($r_s = 0.06$ (95%-CI: −0.10 to 0.21).

Of note, some of these exposure assessment methods were not intended to directly represent total personal RF-EMF exposure, but rather specific exposure situations, such as residential exposure. The geo-coded distance of the residence to the closest fixed site transmitter at home is expected to represent exposure to fixed site transmitters at home. The corresponding correlation between the geo-coded distance and residential exposure to fixed site transmitters measured by the exposimeter was −0.26 (95%-CI: −0.39 to −0.11). The mean residential exposure to fixed site transmitters was calculated using the respective exposimeter measurements at home during the measurement week, identified by the personal diary. Similarly, the correlation between mean personal exposure to fixed site transmitters and the calculated value obtained from the geospatial propagation model was 0.71 (95%-CI: 0.63 to 0.78). The correlation between spot measurements and personal exposure measurements in the bedroom was 0.73 (95%-CI: 0.63 to 0.80).

3.4. Correlations of the different exposure sources

By using the personal exposimeter measurements, we assessed the correlations of the different frequency bands with total exposure and with each other. Total exposure correlated best with exposure to mobile phone handsets ($r_s = 0.42$; 95%-CI: 0.29 to 0.54), mobile phone base stations ($r_s = 0.38$; 95%-CI: 0.24 to 0.50) and cordless phones ($r_s = 0.37$; 95%-CI: 0.23 to 0.49). These were also the sources that contributed most to total mean exposure (Frei et al., 2009b). The Spearman correlations among the different frequency bands were low, with the highest positive correlation between exposure to W-LAN and mobile phone handsets ($r_s = 0.21$; 95%-CI: 0.06 to 0.35) and the most negative correlation between exposure to cordless phones and mobile phone handsets ($r_s = -0.15$; 95%-CI: −0.30 to 0.00). The correlation between exposure to mobile phone handsets and mobile phone base stations was 0.07 (95%-CI: −0.09 to 0.22).

4. Discussion

This study evaluated multiple exposure assessment methods for estimating personal exposure to environmental far-field RF-EMF. Personal mobile and cordless phone use was observed to contribute

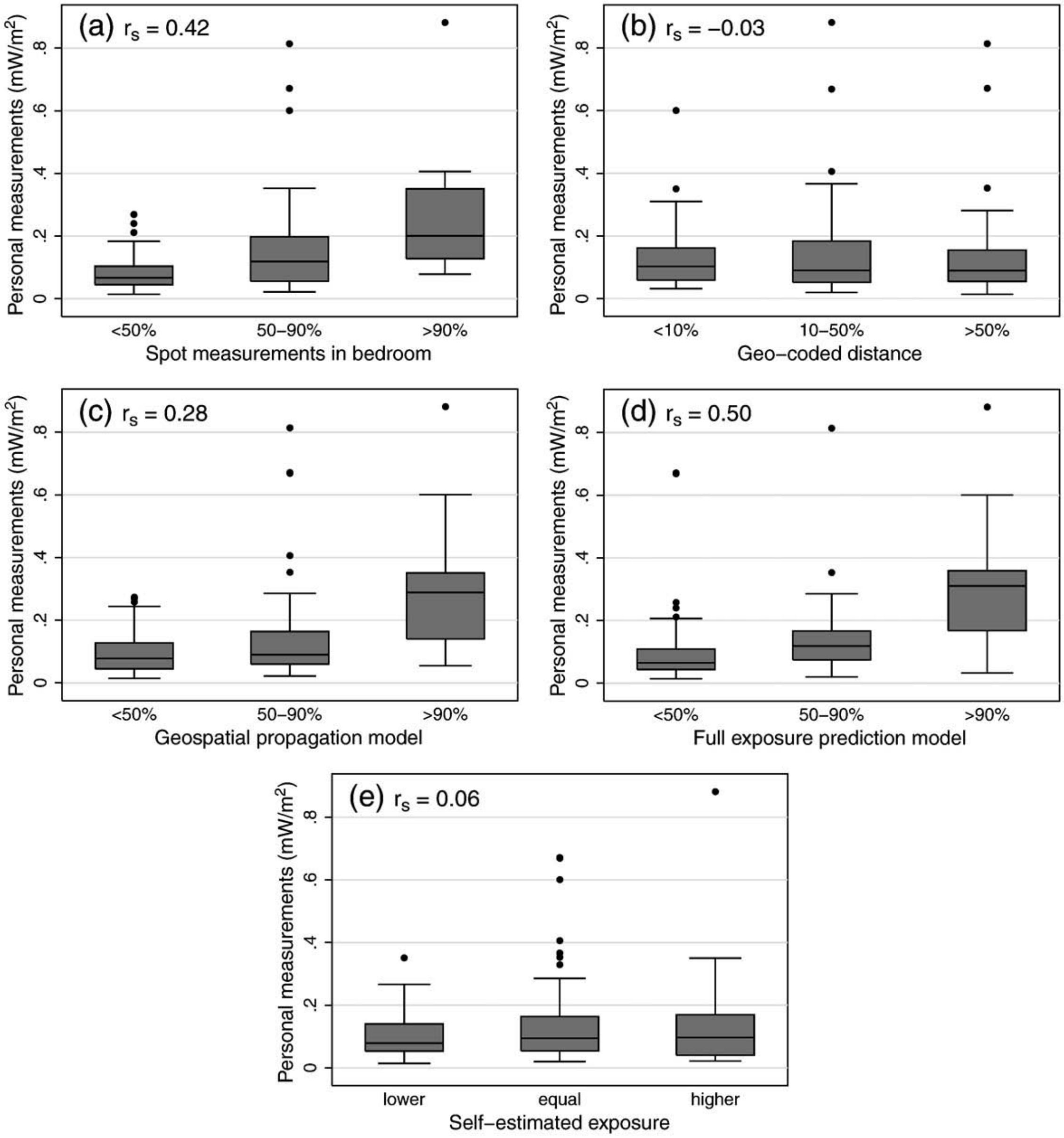

Fig. 3. Box plots of the different exposure assessment methods with the mean total exposure (without personal phone use) in mW/m^2 measured by the exposimeters. Exposure was classified into three groups (<50th percentile, 50–90th percentiles, >90th percentile).

relatively little to the personal RF-EMF measurements, and geo-coded distance to the closest fixed site transmitter and the self-estimated exposure were shown to be inappropriate surrogates for personal RF-EMF exposure. The highest correlation with personal measurements was found for the full exposure prediction model, which takes into account modeled exposure at home and behavioral characteristics of a person, followed by spot measurements in the bedroom and the geospatial propagation model.

4.1. Strengths and limitations

This study consisted of a comprehensive exposure data collection, where approximately 6500 exposimeter measurements were collected over one entire week for 12 different frequency bands per person. In addition, we performed spot measurements, calculated the distance of the residence to the closest fixed site transmitter, collected data on self-estimated exposure, and developed a geospatial propagation model for the study region and a prediction model including personal characteristics. The multiple methods employed for exposure assessment allowed for direct comparison of the different methods, and to the authors' knowledge such an extensive comparison has not been conducted before. The Spearman correlation allowed for evaluating the reliability of the exposure assessment methods to classify exposure levels, and the ranking of exposure levels may be more essential than the correctness of absolute values in epidemiological studies (Neubauer et al., 2007).

Exposimeter measurements require a large organizational effort, thus a small sample size in this study is a primary limitation. In addition, personal exposimeter measurements served as measure of comparison, and measurement accuracy for the different frequency bands may be uncertain. A previous analysis observed that the accuracy of personal exposimeter measurements depended on specific configurations of different services generating different modulations of the signal and that cross-talks between bands may occur (Lauer et al., 2010). In addition, shielding of the body might be of concern and depends on the body mass of a person (Knafl et al., 2008; Neubauer et al., 2008). We tried to minimize this problem by advising the study participants to place the exposimeters in their vicinity, but not directly on the body, when not moving.

To our knowledge, personal exposimeters include the most relevant RF-EMF sources. However, there are additional sources in the radio frequency range which were not considered. Our spot measurements included three additional frequency bands (paging services (147–148 MHz), DAB channel 12 (digital audio broadcast; 223–230 MHz) and GSM-Rail (mobile communication for the railway; 921–925 MHz)). The average contribution of these sources was small (3.3%). We are not aware of other sources in the everyday environment which could have made a relevant contribution to total RF-EMF at the time of the measurement period (in the frequency range of 88–2500 MHz).

4.2. Personal exposure measurements of sources operating close to the body

Mobile and cordless phone radiation is an important exposure source also when personal phone use is omitted from the calculation of mean values (Fig. 2(b)). The high contribution of mobile phone radiation may be mainly explained by the passive exposure from other persons using mobile phones. Also, handovers of the personal mobile phone from one base station to another may be of influence. For cordless phones, the constant radiation of most available cordless phone base stations and cordless phone calls from other persons are explanations for the high contribution.

Exposure to uplink and DECT radiation as well as total exposure increased with increasing use of mobile and cordless phones even if calculated without personal phone use. There are several explanations for this: firstly, some phone calls may not have been noted in the diary, and this might correlate with the amount of phone use. Secondly, regular mobile and cordless phone users might spend more time at crowded places or with persons with similar behaviors in terms of phone use and thus have a higher background exposure to mobile and cordless phone radiation. Thirdly, regular mobile phone users might spend more of their time on the way, for example in trains, which leads to more carry-overs of the personal mobile phone. Fourthly, regular cordless phone users might be near radiating DECT base stations more often.

The high Spearman correlation between the personal measurements with and without personal phone use ($r_s = 0.94$) suggests that mean values derived from all personal measurements including personal phone use do reliably discriminate between participants' exposure levels to environmental far-field sources. This poses an advantage because not having to collect data on phone use reduces the effort for study participants as well as for data management. Although the absolute difference between the two mean total values was small, it was statistically significant. Hence, in a study where one intends to characterize typical exposure levels to environmental far-field sources in a certain population (instead of just differentiating between highly and lowly exposed categories), the use of personal mobile and cordless phones is not negligible. Although small on average, personal mobile and cordless phone use can reach substantial contributions for heavy phone users.

4.3. Evaluation of the exposure assessment methods for epidemiological purposes

In addition to the basic prerequisite to reliably discriminate between participants' exposure levels that an exposure assessment method has to fulfill, there are other aspects which have to be considered for the use in epidemiological studies. Participation bias is of concern. It can be introduced if an exposure assessment method requires active participation from potential study participants, and it is expected to be specifically pronounced if a large effort for study participants is involved. In this case, a substantial part of the study participants might refuse to participate, which may be of major concern if participation is related to both health and exposure statuses (Bakke et al., 1990; de Marco et al., 1994; Röösli, 2008). Collecting exposimeter measurements in combination with diary data is likely to introduce participation bias because of the large effort required for study participants. Spot measurements in bedrooms also rely on compliance of study participants; however, a smaller effort is required. The full exposure prediction model relies on compliance from study participants because it requires questionnaire data from the participants. The effort for completing a questionnaire, however, is highly reduced compared to collecting personal exposimeter measurements. The use of a geospatial propagation model or of the geo-coded distance to the closest fixed site transmitter may be more ideal, because participants do not have to be contacted in order to assess exposure. Our results suggest, however, that the geo-coded distance cannot reliably represent personal exposure. This is in line with previous studies in which the geo-coded distance was compared to spot measurements in the bedroom or personal measurements over 24 h (Bornkessel et al., 2007; Breckenkamp et al., 2008; Radon et al., 2006). However, we found a moderate correlation between the geo-coded distance and residential exposure from fixed site transmitters ($r_s = -0.26$ (95%-CI: -0.39 to -0.11).

Another issue regarding epidemiological studies is information bias. Information bias can be introduced if an exposure assessment method relies on subjective information of the study participants, and if objective exposure data is collected simultaneously with data on health because participants might be aware of the aim of the study. Self-estimated exposure is particularly prone to information bias. That self-estimated exposure is not correlated with actual personal exposure may imply that study participants are not aware of their own RF-EMF exposure status and that they may be considered to be blinded to exposure. Therefore, evaluating self-estimated exposure can offer evidence for the occurrence of information bias and/or of a nocebo effect (which is the inverse of the placebo effect and means that adverse symptoms occur due to expectations (e.g. due to concerns)) (Röösli, 2008). In general, exposure assessment methods which are not based on subjective components are preferred and using the geo-coded distance to the closest fixed site transmitter or a geospatial propagation model fulfills this criterion ideally from this perspective. The full exposure prediction model relies on subjective information of the study participant; however, our model variables relate to statements about the ownership of wireless devices which are unlikely to be heavily biased or predictors which are unlikely to be related to RF-EMF exposure by lay persons (e.g. type of house wall).

The cost and feasibility of an exposure assessment method are also important criteria which have to be taken into account. Methods which involve high costs and workforce are personal exposimeter measurement studies or spot measurements. Typically, only a limited number of study participants can be included in such studies. The development of a geospatial or full exposure prediction model can be costly. Once developed, however, they are applicable for large study populations. The exposure assessment methods which involve low costs are the geo-coded distance or self-estimated exposure.

To date, no information is available on what biological mechanism is relevant for RF-EMF below the standard limits. Scientific evidence has not suggested a health effect resulting from one specific exposure source or type of modulation (Neubauer et al., 2007; Schüz and Mann, 2000). Therefore, we consider it reasonable to take into account exposure from all relevant exposure sources. Our results show that no single exposure source is highly correlated with exposure over all frequency bands, and that the different exposure sources do not correlate with each other. Not including all relevant sources in an epidemiological study would therefore introduce a considerable random error which would lead to a substantial loss of power and to an underestimation of the true exposure–response association (Neubauer et al., 2007). However, it cannot be ruled out that future research might discover that effects are caused by specific exposure sources or that humans are specifically susceptible to RF-EMF during certain times of the day, e.g. during night. If this is the case, a re-evaluation of the exposure assessment methods will have to be conducted.

5. Conclusions

This study provides new insight about the interpretation of different exposure assessment methods used in previous studies. Our data suggest that a reliable discrimination of personal exposure levels to environmental far-field RF-EMFs measured with exposimeters is also made when measurements during personal mobile and cordless phone use are included. The evaluation of other exposure assessment methods showed that spot measurements at home or modeling exposure from fixed site transmitters are conceivable surrogates for personal exposure, particularly for residential exposure. Optimally, data on residential exposure are combined with personal characteristics, as done in our full exposure prediction model. Using the geo-coded distance to the closest fixed site transmitter or self-estimated exposure is inappropriate, but the latter can provide information on a possible information bias or nocebo effect. Due to the rapid change of the technological development, the exposure situation in the everyday environment is expected to change substantially in the future, which means that the use of different exposure assessment methods will have to be re-evaluated.

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Conflict of interest

The authors declare no conflict of interest.

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6 Health effects of RF-EMF exposure

Article 7: Systematic review on the health effects of radiofrequency electromagnetic field exposure from mobile phone base stations

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Abstract

Objective: To evaluate the recent literature on mobile phone base station (MPBS) radiation and health effects.

Methods: We performed a systematic review of human randomized trials conducted in laboratory settings and epidemiological studies that investigated health effects of MPBS radiation in the everyday environment.

Findings: In total, we included 17 articles that fulfilled the basic quality criteria, among them 5 were randomized human laboratory trials and 12 epidemiological studies. The majority of the papers (14) examined self-reported non-specific symptoms of ill health. Most of the randomized trials did not detect any association between MPBS radiation and acute development of symptoms during or shortly after exposure. The sporadically observed associations did not show a consistent pattern in terms of symptoms or types of exposure. For epidemiological studies, we found a pattern that the more sophisticated the exposure assessment was carried out, the less likely an effect was reported. Studies on other health effects than non-specific symptoms as well as investigations in children were scarce.

Conclusion The evidence for a missing relationship between MPBS exposure up to 10 V/m and acute symptom development can be considered strong because it is based on randomized and blinded human laboratory trials. At present, there is insufficient data to draw firm conclusions about health effects from long-term low level exposure typically occurring in the everyday environment.

Introduction

The introduction of mobile phones using the digital GSM (Global System for Mobile Communications) 900 and GSM 1800 systems in the 1990s and the subsequent introduction of UMTS (Universal Mobile Telecommunications System) have led to a wide use of this technology and to a substantial increase in the number of mobile phone base stations (MPBS) all over the world. This development has raised public concerns about potential health effects of the radiofrequency electromagnetic field

(RF-EMF) emissions of this technology (Schreier et al., 2006; Schröttner and Leitgeb, 2008; Blettner et al., 2009), which has generated substantial controversy. A small proportion of the population attributes non-specific symptoms of ill health such as sleep disturbances or headache (Röösli et al., 2004; Schreier et al., 2006) to EMF exposure. This phenomenon is described as electromagnetic hypersensitivity (EHS) or idiopathic environmental illness with attribution to electromagnetic fields (IEI-EMF) (Leitgeb and Schröttner, 2003; Rubin et al., 2005; 2006; Röösli, 2008). Additionally, EHS individuals often claim to be able to perceive RF-EMF in their daily life (Röösli, 2008).

The population is generally exposed to MPBS radiation under far-field conditions, resulting in a relatively homogenous whole-body exposure. This exposure can occur continuously but the levels are considerably lower than local maximum levels that occur when using a mobile phone handset (Neubauer et al., 2007). A recent personal RF-EMF measurement study in a Swiss population sample demonstrated that on average the exposure contribution from MPBS is relevant for the cumulative long-term whole-body RF-EMF exposure. However, as expected, it is of minor importance for the cumulative exposure of the head of regular mobile phone users (Frei et al., 2009b).

In 2005, the World Health Organization (WHO) organized a workshop on the exposure and health consequences of radiation from MPBSs and subsequently published a paper about the state of knowledge (Valberg et al., 2007). At that time, studies about the health impact of MPBS emissions were scarce and of low quality, because most of the previous RF-EMF health research had focused on exposure to mobile phone handsets and outcomes related to exposure of the head such as brain tumours or brain physiology. In the last four years, research efforts have increased in response to complaints from the population and stimulated by a Dutch study describing decreased well-being in association with UMTS base station exposure (Zwamborn et al., 2003). Acute effects have been investigated in healthy volunteers and EHS individuals using randomized, blinded laboratory trials as well as field intervention studies. Epidemiological research has been stimulated thanks to the recent availability of personal exposure meters.

The aim of this paper is to systematically review the scientific literature concerning the effects of MPBS radiation on all health effects that have been investigated so far.

Methods

Literature search

A systematic literature search was performed in March 2009 including all articles published before this date. We searched the electronic databases Medline, EMBASE, ISI Web of Knowledge, and the Cochrane Library to identify all relevant peer-reviewed papers. Key and free text words included “cellular phone”, “cellular”, “phone”, “mobile”, “mobile phone” in combination with “base station(s)”. The search was complemented with references from the specialist databases ELMAR (http://www.elmar.unibas.ch) and EMF-Portal (http://www.emf-portal.de) and by scrutinizing the reference lists of relevant publications. Additionally, published reports from national EMF and mobile phone research programs were eligible for inclusion.

Inclusion and exclusion criteria

We included human laboratory trials and epidemiological studies. We considered all health effects that have been addressed so far. These include self-reported non-specific symptoms (e.g. headache, sleep disturbances, concentration difficulties), physiological measures (e.g. hormone levels, brain activity), cognitive functions, genotoxicity, cancer and other chronic diseases. In addition, we included randomized double blind trials evaluating whether study participants were able to perceive the RF-EMF exposure. For a study to be eligible, far-field exposure from MPBS had to be investigated; i.e. a relatively homogenous whole-body field in the GSM 900, GSM 1800 or UMTS frequency range. The relationship between exposure and outcome had to be statistically quantified. In addition, basic quality criteria had to be fulfilled. Trials had to apply at least two different exposure conditions in a randomized and blinded way. Epidemiological studies had to quantify the exposure using objective exposure measures (such as measured distance to the next MPBS, spot or personal exposure measurements, or modelling), possible confounders had to be considered, and the selection of the study population had not to be obviously biased, i.e. related to both, exposure and outcome.

Data extraction

The data of each study were extracted independently by two researchers by means of two standardized forms, one for randomized trials and one for epidemiological studies. These forms were developed using the CONSORT statement (Moher et al., 2001) for trials and the STROBE statement (Vandenbroucke et al., 2007) for epidemiological studies. Extracted data included information about study participants, selection procedure, study design, exposure, analytic methods, results and quality aspects. Differences in data extraction were resolved by consensus.

Meta-analysis

All reported outcomes were checked for suitability for a meta-analysis. The only outcome with a sufficient number of comparable studies was the ability to perceive RF-EMF exposure. In order to combine these study results, we calculated for each study the difference between the number of observed correct answers (O) and the number of expected correct answers by chance (E), normalized by the number of expected correct answers by chance ((O-E)/E). Exact 95% confidence intervals were calculated based on binomial or Poisson data distribution, depending on the experimental design. In the absence of heterogeneity between studies ($p=0.99$; $I^2=0.0\%$), we used fixed-effect models for pooling the study estimates. The detailed method is described in Röösli (2008).

Evidence rating

In order to rate the evidence for detrimental health effects from MPBS, we assessed the risks of various types of bias for all included studies as proposed by the Cochrane Handbook (Higgins and Green, 2009). Final evidence rating was conducted according to the GRADE approach (Atkins et al., 2004).

Results

Selection of studies

In total, 134 potentially relevant publications were identified and 117 articles were excluded as they did not meet our inclusion criteria (Figure 6-1). Seventeen articles were included in the analyses, of which 5 were randomized trials and 12 were epidemiological or field intervention studies. The majority of the studies examined non-specific symptoms.

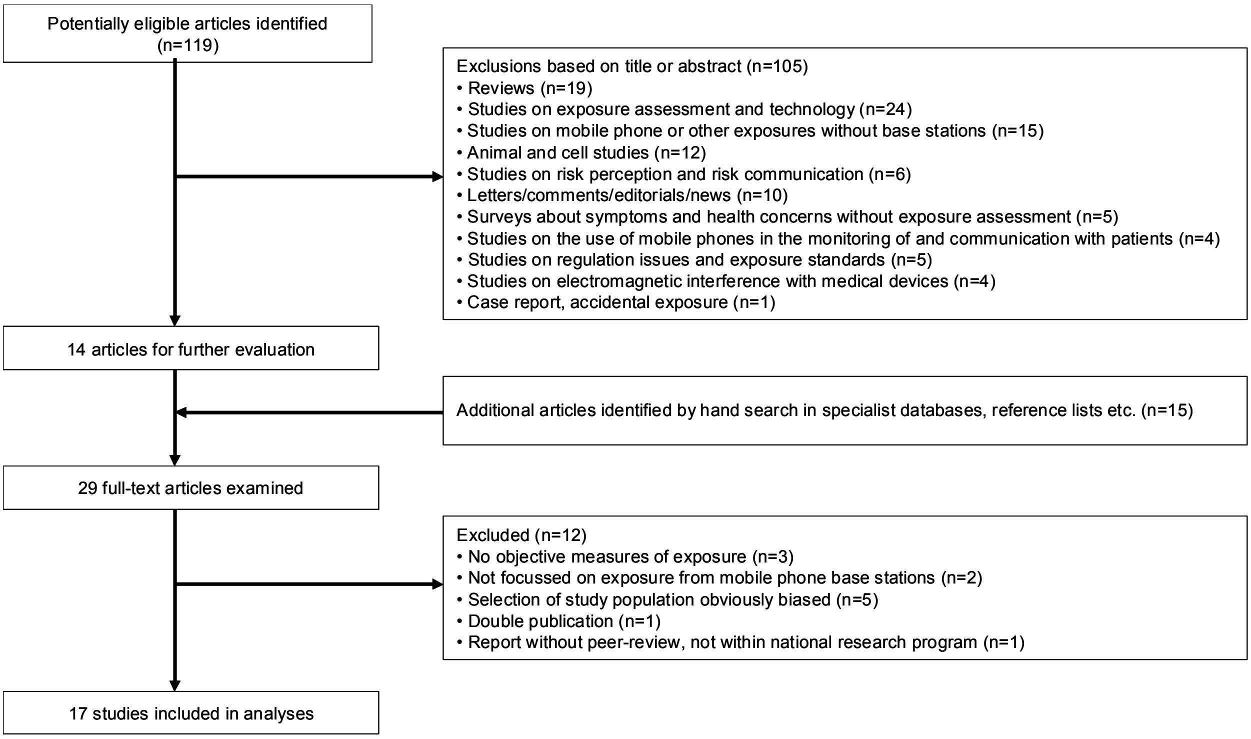

Figure 6-1: Overview about the identification of eligible studies and the selection of included studies. (For a detailed flow chart showing all references, see supplementary material on the web).

Non-specific symptoms of ill health

Acute effects of MPBS exposure on self-reported non-specific symptoms were investigated in four randomized double-blind human laboratory trials. The details of these studies are summarized in web table 6-1. Three trials used a UMTS antenna for creating controlled exposure circumstances (Regel et al., 2006; Riddervold et al., 2008; Furubayashi et al., 2009), and one study evaluated all three mobile phone frequency bands (Eltiti et al., 2007a). In total, 282 healthy adults, 40 healthy adolescents and 88 EHS individuals were included in these four studies. Exposure levels varied between 0.9 and 10 V/m.

We identified ten epidemiological studies investigating the effect of MPBS exposure on self-reported non-specific symptoms (web table 6-2). Most of these studies were of cross-sectional design and exposure quantification was either based on the distance between place of residence and the next MPBS (Abdel-Rassoul et al., 2007; Blettner et al., 2009), spot measurements of MPBS radiation in the bedroom (Hutter et al., 2006; Berg-Beckhoff et al., 2009), or 24h personal measurements of RF-EMF exposure (Thomas et al., 2008a; Kühnlein et al., 2009). Four epidemiological studies applied an experimental approach (field intervention) either by turning on and off a MPBS (Heinrich et al., 2007; Danker-Hopfe et al., 2008) or by using shielding curtains to generate exposure differences (Leitgeb et al., 2008; Augner et al., 2009). Study sizes ranged from 43 to 26,039 participants. The cut-off values, differentiating exposed from unexposed persons, varied between 0.1 and 0.43 V/m.

Of all non-specific symptoms, headache was most often investigated (Table 6-1). Two epidemiological studies (Hutter et al., 2006; Abdel-Rassoul et al., 2007) reported a statistically significant positive correlation between exposure level and headache score. In a Danish laboratory trial, the change in headache score was larger during UMTS exposure than during sham condition when the data from 40 adults and 40 adolescents were pooled (Riddervold et al., 2008). However, further analyses indicated that this change was rather due to a lower baseline score prior to the UMTS exposure than due to a higher score after the exposure. The remaining four epidemiological studies (Heinrich et al., 2007; Thomas et al., 2008a; Berg-Beckhoff et al., 2009; Kühnlein et al., 2009) and one laboratory trial (Regel et al., 2006) did not indicate any association between mobile MPBS exposure and headache.

With respect to self-reported sleep measures, only the Egyptian study (Abdel-Rassoul et al., 2007) reported a higher daytime fatigue in exposed individuals. All other studies did not indicate any relation between MPBS exposure and fatigue or self-reported sleep disturbances (Table 6-2) (Hutter et al., 2006; Danker-Hopfe et al., 2008; Leitgeb et al., 2008; Thomas et al., 2008a; Berg-Beckhoff et al., 2009; Furubayashi et al., 2009; Kühnlein et al., 2009).

Many other non-specific symptoms have been evaluated such as concentration difficulties or dizziness. Mostly, no association with exposure was observed (details see web tables 6-1 and 6-2). Among the few exceptions, there was one laboratory trial which showed an increased arousal score in the EHS group during UMTS exposure, which may be partly explained by the unbalanced order of exposures (Eltiti et al., 2007a). One field intervention study observed a small increase in calmness during the unshielded condition compared to the shielded condition, but no effect on mood and alertness (Augner et al., 2009). In an observational study from Egypt, several symptoms were more prevalent in 85 inhabitants or employees of a house near a MPBS compared to 80 employees considered unexposed (Abdel-Rassoul et al., 2007). In an Austrian study with 365 participants, three out of 14 symptoms (headache, cold hands and feet, concentration difficulties) were statistically significantly related to exposure from MPBS (Hutter et al., 2006).

Some studies evaluated overall symptom scores obtained from standardized questionnaires such as SF-36, “von Zerssen list” or “Frick symptom score” (Table 6-3). In a survey of 26,039 German residents, the Frick symptom score was significantly elevated for people living less than 500 m from a MPBS compared to those living further away (Blettner et al., 2009). However, subsequent improved dosimetric evaluations in 1,326 randomly selected volunteers of this survey did not confirm a relation between symptoms and measured MPBS radiation (Berg-Beckhoff et al., 2009). Three additional studies also did not confirm any association between exposure and symptom scores (Regel et al., 2006; Eltiti et al., 2007a; Heinrich et al., 2007).

In summary, considering all randomized trials and epidemiological studies together, no single symptom or symptom pattern was consistently related to exposure. The cross-sectional epidemiological studies showed a striking pattern that studies with crude exposure assessments based on distance showed health effects whereas studies based on exposure measurements did not indicate any association.

Table 6-1: Studies on mobile phone base station radiation and self-reported headache

Reference	Study design	Collective	Exposure source	Exposure level of the exposed group(s)	Outcome measure	Results
Randomized human laboratory studies						
Regel 2006	Cross-over	33 EHS and 84 non EHS adults	UMTS	1 and 10 V/m	One item of the Bulpitt quality of life questionnaire	No exposure-outcome relation: $p=0.41$
Riddervold 2008	Cross-over	40 adults and 40 adolescents	UMTS	0.9 to 2.2 V/m	VAS scale $^{\alpha}$	Change of headache score during exposure: $p=0.03$
Epidemiological studies						
Hutter 2006	Cross-sectional	365 randomly selected participants living in the vicinity of mobile phone base stations	GSM 900	>0.43 V/m	Item of Zerssen symptom list	RR=3.1 (95%-CI: 1.2; 7.7)
Abdel-Rassoul 2007	Cross-sectional	165 adults living/working near or far away from a mobile phone base station	Not specified	Not reported	Questionnaire $^{\alpha}$	OR=2.8 (95%-CI: 1.1; 7.4)
Heinrich 2007	Field intervention	95 employees in an office building	UMTS	0.1 V/m	Questionnaire $^{\alpha}$	Mean score unexposed: 0.128 (SD=0.588) Exposed: 0.152 (SD=0.615)
Thomas 2008	Cross-sectional	329 randomly selected adults	All $^{\beta}$	0.21 to 0.58% of ICNIRP limit $^{\gamma}$	Freiburg symptom score	OR=1.2 (95%-CI: 0.2; 6.4)
	Longitudinal			0.19–0.56% (morning) 0.22–0.71% (afternoon) of ICNIRP limit $^{\gamma}$	Item of Zerssen symptom list	Morning: OR=0.6 (95%-CI: 0.1; 2.8) Afternoon: OR= 3.1 (95%-CI: 0.8; 12.6)
Berg-Beckhoff 2009	Cross-sectional	1326 randomly selected adults	Base station (sum of GSM 900, GSM 1800 and UMTS)	>0.1 V/m	HIT-6	Score decrease in exposed individuals: -0.24 (95%-CI: -1.57; 1.08)
Kühnlein 2009	Cross-sectional	1433 randomly selected children	All $^{\beta}$	>90th percentile (value not reported)	Item of Health Behavior in School-Aged Children question-	Headache: OR=0.6 (95%-CI: 0.3; 1.0)

$^{\alpha}$ no information about validation is given
$^{\beta}$ sum of GSM 900, GSM 1800, UMTS (up- and downlink), DECT and WLAN
$^{\gamma}$ 0.21% of ICNIRP limit corresponds to 0.123 V/m at a frequency of 1800 MHz

Field perception

Four randomized double-blind trials addressed the ability to perceive the presence of RF-EMF exposure. None of these trials (Regel et al., 2006; Eltiti et al., 2007a; Riddervold et al., 2008; Furubayashi et al., 2009) revealed a correct field detection rate better than expected by chance (Figure 6-2) and there was no evidence that EHS individuals were more likely to correctly determine the presence or absence of the exposure than non-EHS individuals (p=0.66).

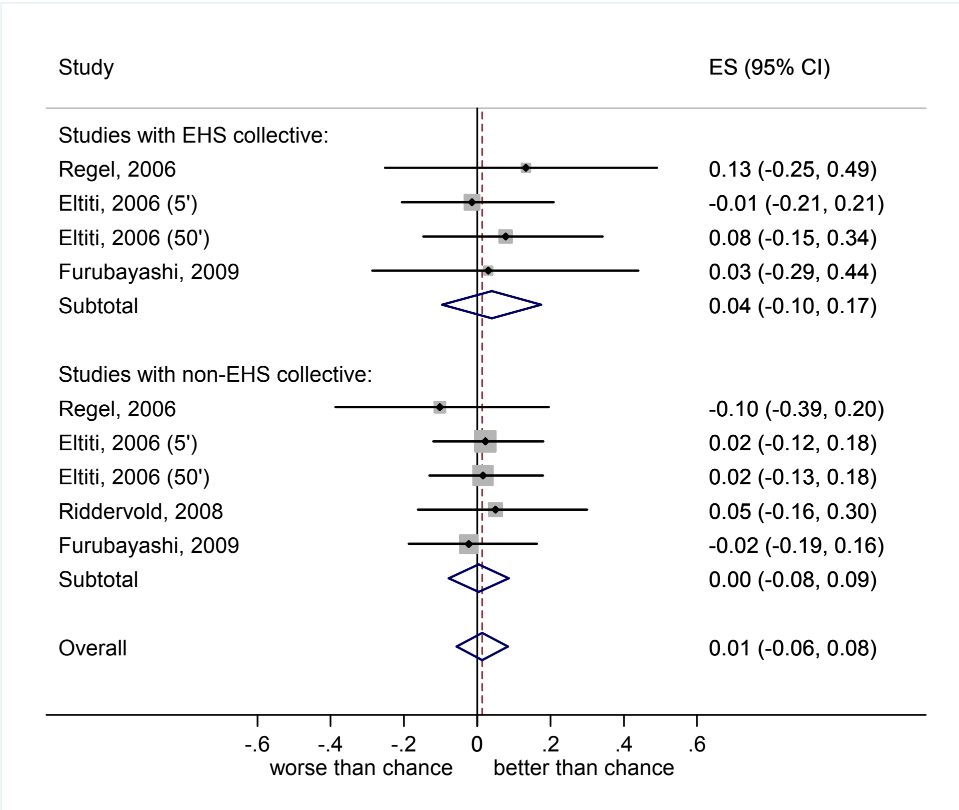

Figure 6-2: Graphical representation of the results from the field detection tests by means of randomized double blind trials carried out in laboratory settings. Effect size (ES) refers to the relative difference between observed and expected correct answers. The edges of the diamonds show the 95% confidence intervals of the pooled estimates (subtotal, overall).

Furthermore, in the German field intervention study (Heinrich et al., 2007), a newly installed MPBS on top of an office building was randomly turned on and off over a period of 70 working days and the employees estimated its operation status every evening. The most successful participant achieved 69% correct answers in 42 ratings. The likelihood to achieve such or a better performance by chance is 1%. To observe one study participant out of 95 with such a success rate can be expected by chance.

Cognitive functions

Exposure effects on cognitive functions were investigated in three trials (Regel et al., 2006; Riddervold et al., 2008; Furubayashi et al., 2009). and two epidemiological studies (Hutter et al., 2006; Abdel-Rassoul et al., 2007). All three trials applied an UMTS base station exposure. No exposure effect was observed in a variety of cognitive tests. The Egyptian study produced inconsistent results (Abdel-Rassoul et al., 2007), whereas the Austrian study showed no exposure effects in several cognitive tests (Hutter et al., 2006).

Physiological measures

Three laboratory studies investigated different physiological responses. In one trial, no significant changes on blood volume pulse, skin conductance and heart rate were observed in 44 EHS individuals and 115 non-EHS individuals due to GSM 900, GSM 1800 or UMTS base station exposure (Eltiti et al., 2007a). Likewise, autonomic nervous functions as measured by skin surface temperature, heart rate, and local blood flow in the finger tip were not altered due to UMTS base station exposure in a Japanese study (Furubayashi et al., 2009). In the third trial, polysomnographic EEG recordings of 13 study participants exposed to a GSM 1800 base station field during two nights did not differ significantly from the respective recordings of two sham nights (Table 6-2) (Hinrichs et al., 2005). In two field intervention studies, polysomnographic measures were not related to exposure (Danker-Hopfe et al., 2008; Leitgeb et al., 2008).

Genotoxicity, cancer and other chronic diseases

One observational study addressed genotoxic effects of MPBS radiation. The investigators compared blood samples from 38 radio field engineers of two Belgian mobile phone operators and 11 administrative workers who were exposed at their workplace to RF antennas from surrounding buildings with 25 subjects who were unrelated to the operators, had occupations that excluded exposure to RF-EMF sources and did not use a mobile phone (Maes et al., 2006). Overall, no differences

Table 6-2: Studies on mobile phone base station radiation and self-reported sleep measures as well as polysomnographic recordings.

Reference	Study design	Collective	Exposure source	Exposure level of the exposed group(s)	Outcome measure	Results
Randomized human laboratory studies						
Hinrichs 2005	Cross-over	13 healthy volunteers	GSM 1800	30 V/m at subject's head	Polysomnography	No significant effects on classical sleep parameters
Furubayashi 2009	Cross-over	11 female EHS and 43 female controls	W-CDMA (2140 MHz)	10 V/m at subject's head	POMS (Profile of Mood States) questionnaire	Effect of condition: Fatigue (p=0.41)
Epidemiological studies						
Hutter 2006	Cross-sectional	365 randomly selected participants living in the vicinity of mobile phone base stations	GSM 900	>0.43 V/m	Pittsburgh Sleep Quality Index (PSQI)	Sleep quality: p=0.24 Sleep disturbances: p=0.34 Global sleep score: p=0.28
Abdel-Rassoul 2007	Cross-sectional	165 adults living/working near or far away from a mobile phone base station	Not specified	Not reported	Questionnaire	Sleep disturbances: OR=2.8 (95%-CI: 1.1; 7.4)
Danker-Hopfe 2008	Field intervention	397 adults from 10 German towns	GSM 900/ GSM 1800 base station	0.1 V/m	Sleep diary and polysomnography	Sleep efficiency: p=0.84 Time spent in bed: p=0.29 Total sleep time: p=0.39 Sleep latency: p=0.83 Wake after sleep onset: p=0.88 Restfulness: p=0.59
Leitgeb 2008	Cross-sectional	43 EHS volunteers from Germany and Austria	All sources	Unshielded condition: about 0.5% of ICNIRP limit	Written questionnaire on subjective sleep quality	Non-significant improvement of sleep score with increasing GSM-EMF at baseline (p>0.05)
	Field intervention		Shielding of RF-EMF during 3 nights	Shielding	Polysomnography	No statistical significant effects on sleep parameters

Table 6-2 (continued)

Reference	Study design	Collective	Exposure source	Exposure level of the exposed group(s)	Outcome measure	Results
Thomas 2008	Cross-sectional	329 randomly selected adults	All[α]	0.21 to 0.58% of ICNIRP limit	Freiburger Beschwerdeliste	Sleeping disorders: OR=1.1 (95%-CI: 0.5; 2.1) Fatigue: OR=0.7 (95%-CI: 0.3; 1.8)
	Longitudinal (within one day)			0.19–0.56% (morning) 0.22–0.71% (afternoon) of ICNIRP limit	Fatigue (item of Zerssen symptom list)	Morning: OR=0.5 (95%-CI: 0.2; 1.1) Afternoon: OR=0.5 (95%-CI: 0.3; 1.0)
Berg-Beckhoff 2009	Cross-sectional	1326 randomly selected adults	Base station (sum of GSM 900, GSM 1800 and UMTS)	>0.1 V/m	Pittsburgh Sleep Quality Index (PSQI)	Score difference: -0.15 (95%-CI: -0.69; 0.38)
Kühnlein 2009	Cross-sectional	1433 randomly selected children	All[α]	>90th percentile (value not reported)	Items of the Health Behavior in School-Aged Children Questionnaire	Sleeping problems: OR=1.0 (95%-CI: 0.6; 1.5) Fatigue: OR=0.8 (95%-CI: 0.6; 1.3)

[α] sum of GSM 900, GSM 1800, UMTS (up- and downlink), DECT and WLAN in the chromosomal aberrations, DNA damage and sister chromatid exchange frequency were found between the three groups. There was a tendency towards increased chromatid breaks for field engineers compared to administrative workers and control persons.

An ecological study compared the cancer incidence of 177,428 persons living in 48 municipalities in Bavaria between 2002 and 2003 in terms of MPBS coverage (Meyer et al., 2006). A crude three level exposure classification was applied to each municipality based on the transmission duration of each MPBS and the proportion of the population living closer than 400 m to a MPBS. No indication of an increased cancer incidence in municipalities belonging to the highest exposure class was observed for all types of tumours combined. The number of cases was too small for tumour specific analyses.

We identified no study investigating other chronic diseases than cancer with respect to MPBS exposure.

Discussion

In response to public concerns, most studies dealing with RF-EMF exposure from MPBSs investigated non-specific symptoms of ill health including self-reported sleep disturbances. The majority of these studies did not indicate acute occurrence of symptoms when being exposed to GSM 900, GSM 1800 or UMTS fields from MPBSs. The sporadically observed associations in randomized laboratory trials did not show a consistent pattern in terms of symptoms or types of exposure. For epidemiological studies we found that the more sophisticated the exposure assessment was carried out, the less likely an effect was reported. We also found no evidence that EHS individuals are more susceptible to MPBS radiation than the rest of the population.

Table 6-3: Studies on mobile phone base station radiation and symptom scores obtained from quality of life questionnaires.

Reference	Study design	Collective	Exposure source	Exposure level of the exposed group(s)	Outcome measure	Results
Randomized human laboratory studies						
Regel 2006	Cross-over	33 EHS and 84 non EHS adults	UMTS	1 and 10 V/m	Change of current disposition during exposure (CDdiff), CD after exposure (CDpost), adapted quality of life questionnaire (TNO)	No exposure-outcome relation in EHS/non-EHS persons CDdiff: p=0.95/ p=0.95 CDpost: p=0.96/ p=0.89 TNO: p=0.65 /p=0.92
Eltiti 2007	Cross-over	44 EHS and 115 non-EHS adults	GSM 900, GSM 1800 and UMTS	2 V/m	6 items on a VAS scale	GSM vs. sham in EHS/non-EHS: $^{\alpha}$ Total number of symptoms: p=0.49/ p=0.96 Symptom score: p=0.81/ p=0.49 UMTS vs. sham in EHS/non-EHS: $^{\alpha}$ Total number of symptoms: p=0.10/ p=0.41 Symptom score: p=0.12/ p=0.87
Epidemiological studies						
Heinrich 2007	Field intervention	95 employees of an office building	UMTS	0.1V/m	Questionnaire	During exposure: non-significant increase of symptom score (p=0.08) Cumulative exposure not associated with symptom score (p=0.42)
Blettner 2009	Cross-sectional	26,039 German residents of a panel survey	Geo-coded distance to the closest mobile phone base station	Next base station<500m vs. >500m	Frick symptom score	Score difference: 0.34 (96%-CI: 0.32;0.37)
Berg-Beckhoff 2009	Cross-sectional	1326 randomly selected adults	Base station (sum of GSM 900, GSM 1800 and UMTS)	>0.1 V/m	Zerssen symptom list, SF-336	Score differences: Zerssen: 0.55 (95%-CI: -1.05; 2.15) SF-36, physical: -0.14 (95%-CI: -1.80; 1.51) SF-36, mental: 0.37 (95%-CI: -0.93; 1.68)

$^{\alpha}$ P-values calculated from F and t values. Relevant p-value for significance after Bonferroni correction: p<0.003

Our findings corroborate previous reviews on RF-EMF exposure and self-reported non-specific symptoms (Rubin et al., 2005; Seitz et al., 2005; Valberg et al., 2007; Röösli, 2008; Kundi and Hutter, 2009), while we included a number of more sophisticated recently published studies. In web table 6-3 the risks of various types of bias are shown for all studies included in the review. In tendency, risks of bias were rare in the randomized trials applying controlled exposure conditions in a laboratory in a double blind manner. For epidemiological studies exposure assessment is a challenge, and random exposure misclassification is likely to have occurred in these studies. The corresponding bias is expected to dilute an exposure-response association, if one existed. None of the studies applied long-term exposure measurements. Cross-sectional studies may be informative for effects of prolonged MPBS exposure if the applied measures do represent the exposure level over a longer time period, which is the case according to a Swiss personal RF-EMF measurement study (Frei et al., 2009b). Nevertheless, cross-sectional studies are by design limited in elucidating causal relationships. For self-reported outcomes, information bias could create spurious exposure-outcome associations if study participants are aware of their exposure status. This has to be expected if exposure is assessed using distance to a visible transmitter instead. In this case also selection bias is of concern since affected people who feel being exposed may be more likely to participate in a study. In fact, the objectively measured distance to a MPBS is only weakly correlated to the actual exposure from the corresponding MPBS (Bornkessel et al., 2007; Viel et al., 2009b). Interestingly, in our review the strongest effects on symptoms were observed in two studies using measured distance (Abdel-Rassoul et al., 2007; Blettner et al., 2009) which makes these findings arguable as well.

We excluded three epidemiological studies suggesting a link between cancer incidence and proximity to MPBS (Eger et al., 2004; Wolf and Wolf, 2004; Eger and Neppe, 2009) and three studies indicating an association with non-specific symptoms (Santini et al., 2002; Navarro et al., 2003; Santini et al., 2003) because they did not fulfil our quality criteria. Data collection (Eger et al., 2004; Wolf and Wolf, 2004; Eger and Neppe, 2009) or selection of study participants (Navarro et al., 2003) was obviously related to exposure and outcome and therefore biased. Two studies did not use objective but self-estimated distance as an exposure measure

(Santini et al., 2002; Santini et al., 2003). This is problematic because it is likely to be biased in combination with self-reported symptoms.

Exposure levels in human laboratory studies varied between 1 and 10 V/m. A homogenous UMTS field of 1 V/m is calculated to yield an average whole-body specific absorption rate (SAR) of 6 μW/kg and a 1 gram peak SAR in the brain of 73 μW/kg (Regel et al., 2006). This is considerably lower than peak SARs caused by mobile phone handsets with about 1 to 2 W/kg (Christ and Kuster, 2005). Thus, regarding acute effects related to the brain (e.g. headaches or brain physiology), one would rather expect effects in studies applying mobile phone handset exposure than in studies mimicking MPBS exposures. Studies on mobile phone exposure suggest effects on the EEG alpha band during sleep (Valentini et al., 2007) with some evidence for a dose-response relationship (Regel et al., 2007), but the results are inconsistent regarding cognitive functions (Barth et al., 2008) and mostly negative for headache (Oftedal et al., 2007; Hillert et al., 2008).

Of note, persons classified as highly exposed in the epidemiological studies were actually exposed to rather low field levels. Exposure cut-points for the highest exposed groups were below 0.5 V/m in all studies. This is much lower than the ICNIRP reference levels which range between 41 and 61 V/m for the frequency bands of MPBS (ICNIRP, 1998). Since the exposure of the population seems to be considerably lower than the ICNIRP reference levels, it is currently difficult to investigate long-term health effects of exposure close to the ICNIRP reference levels.

In conclusion, the present research does not indicate an association between any health outcome and RF-EMF exposure from MPBS at levels typically encountered in our everyday environment. The evidence for a missing relation between MPBS exposure and acute symptom development can be considered strong according to the GRADE approach (Atkins et al., 2004) because it is based on randomized trials applying controlled exposure conditions in a laboratory. Regarding long-term effects, data are scarce and the evidence for the absence of long-term effects is limited. Also, only few data for children and adolescents are available and the question of a potential risk for children remains unresolved. In case of scarce data, absence of evidence for harm must not be interpreted as evidence for the absence of harm.

Further research should focus on long-term effects and also include children and adolescents. Additional cross-sectional studies are of limited value and future studies should apply a longitudinal design. Because there is no evidence that potential health effects would be restricted to MPBS frequency bands (Neubauer et al., 2007), we recommend to include assessment of exposure to other RF-EMF sources of daily life such as mobile and cordless phones or wireless LAN (Frei et al., 2009a).

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Web table 6-1: Overview on randomized human laboratory trials of mobile phone base station exposure addressing self-reported non-specific symptoms

Reference	Study design	Collective	Inclusion/ exclusion criteria	Outcome	Exposure setting	Statistical model-covariables	Results (exposure vs. sham/control)
Regel 2006	Cross-over	33 EHS Mean age: 38 y Female: 58%	Incl.: between 20 and 60 years of age, right-handed, and BMI between 19–30 kg/m² Excl.: medical problems, implants, drug consumption	Questionnaires: CDdiff, CDpost, Bulpitt	3*45 min with a) sham b) UMTS (2140 MHz), 1 V/m c) UMTS (2140 MHz), 10 V/m Randomized, counter-balanced	Mixed linear models; circadian rhythm, smoking, exposure order, age, sex, BMI, caffeine intake, medication, (pre-) menstrual complaints, sleep quality, and suffering from a cold.	No exposure-outcome relation: CDdiff (p=0.95) CDpost (p=0.96) Bulpitt (p=0.65)
		84 non EHS Mean age: 38 y Female: 51%					No exposure-outcome relation: CDdiff (p=0.95) CDpost (p=0.89) Bulpitt (p=0.92)
Eltiti 2007	Cross-over	44 EHS Mean age: 46.1 y Female: 42.9%	Excl.: brain injury, epilepsy, claustrophobia, pacemakers, mental disease, psychoactive medication 4 months prior to testing	Rating of 6 items on a VAS scale every 5 minutes: anxiety, tension, arousal, relaxation, discomfort, fatigue	3*50 min with a) sham b) UMTS at 2020 MHz c) GSM 900 and 1880 MHz combined; E-field: 2 V/m Randomized, not counter-balanced	ANOVA; condition, group[1]	GSM: anxiety (p=0.06); tension (p=0.09); arousal (p=0.03); inverse of relaxation (p=0.46); total number of symptoms (p=0.49); symptom score (p=0.81)[1] UMTS: anxiety (p=0.005); tension (p=0.004); arousal (p=0.001); inverse of relaxation (p=0.03); total number of symptoms (p=0.10); symptom score (p=0.12)[1]
		115 non-EHS Mean: 54.5 y, Female: 42.5%					GSM: anxiety (p=0.53); tension (p=0.47); arousal (p=0.83); inverse of relaxation (p=0.25); total number of symptoms (p=0.96); symptom score (p=0.49)[1] UMTS: anxiety (p=0.04); tension (p=0.11); arousal (p=0.46); inverse of relaxation (p=0.04); total number of symptoms (p=0.41); symptom score (p=0.87)[1]
Ridervold 2008	Cross-over	40 healthy adolescents Age range: 15-16 y	Excl: pregnancy, medical history of head injuries and/or neurological or psychiatric diseases, illiteracy	11 symptoms on a VAS scale: Primary outcome: change in headache during session, Secondary outcome: change in concentration difficulties during session	4*45 min with a) sham b) Continuous wave at 2140 MHz c) UMTS signal at 2140 MHz d) UMTS signal at 2140 MHz with all control features E-field: 0.9-2.2 V/m Randomized, counterbalanced	Only exposure (UMTS with all control features) was considered Standard crossover analysis technique based on Wilcoxon test; order of exposure	Concentration: no change (p=0.88) Headache: trend of increase (p=0.09)[2]
		40 healthy adults Age range: 25-40 y Female: 40%					Concentration: increase (p=0.048) Headache: trend of increase (p=0.15)[2]

Web table 6-1 (continued)

Refe-rence	Study design	Collective	Inclusion/ exclusion criteria	Outcome	Exposure setting	Statistical model-covariables	Results (exposure vs. sham/control)
Furubay-ashi 2009	Cross-over	11 female EHS Mean age: 37 y, 43 female con-trols Mean age: 38 y,	Incl: 20 to 60 years Excl: Living too far from Tokyo, myocardial infarction, epilepsy, brain injury, pace-makers, hear-ing aids, preg-nancy, medical treatment for psychiatric disorders	POMS questionnaire: Change of 6 scales dur-ing session: tension-anxiety, depression, an-ger-hostility, vigor, fatigue and confusion. Discom-fort was asked every 5 minutes during exposure	4*30 min W-CDMA (2140 MHz): a) continuous b) intermittent (turned on/off every 5 min), c) sham with noise d) sham without noise E-field: 10 V/m at subject's head Randomized, counter-balanced	ANOVA; condition, se-quence, group, time (be-fore-after) (for discom-fort: condition, group)	Effect of condition: Tension-anxiety (p=0.60) Depression (p=0.78) Anger-hostility (p=0.47) Vigor (p=0.96) Fatigue (p=0.41) Confusion (p=0.77) Discomfort (p=0.86)

Footnotes:
[1] P-values calculated from F and t values. Relevant p-value for significance after Bonferroni correction: $p < 0.003$
[2] Pooled analyses of headache for adolescents and adults resulted in a significant change during exposure (p=0.027)

Abbreviations:
ANOVA: Analysis of variance; Bulpitt: adapted Bulpitt symptom score; CDdiff: change of current disposition during exposure , CDpost: current disposition after exposure, EHS: Electromagnetic hypersensitivity; GSM: Global System for Mobile Communications; HIT-6: Hedache Impact Test; POMS: Profile of Mood States; PSQI: Pittsburgh Sleep Quality Index; UMTS: Universal Mobile Telecommunications System VAS: Visual analogue scale; W-CDMA: Wideband Code Division Multiple Access

Web table 6-2: Overview on epidemiological studies of mobile phone base station exposure addressing self-reported non-specific symptoms. (Abbreviations see below)

Reference	Study design	Study collective (participation rate)	Inclusion/exclusion criteria	Outcome	Exposure assessment	Statistical models; covariables	Results
Hutter 2006	Cross-sectional	365 subjects from Vienna and Carinthia in the vicinity of 10 base stations Mean age: 44 y (range: 18-91 y) Female: 59% (Participation rate: approx. 60% in Vienna, 68% in Carinthia)	Incl.: age >18 y, living in the present house for at least one year and staying there for a minimum of 8 hours a day on average	Zerssen complaint list, PSQI	Spot measurements in the bedroom Main source was GSM 900 3 exposure categories: <0.19 V/m, 0.19-0.43 V/m, >0.43 V/m	ANCOVA for PSQI, logistic regression for Zerssen complaint list; age, sex, region, regular use of mobile telephone and fear of adverse effects of the base station	Highest vs. lowest exposure levels: Headache: RR=3.1 (1.2; 7.7) Cold hands or feet: RR=2.6 (1.2; 5.7) Difficulties in concentration: RR=2.6 (1.1; 6.1). Remaining 11 symptoms and sleep quality measures not associated with exposure.
Abdel-Rassoul 2007	Cross-sectional	85 exposed inhabitants/employees (living near a mobile phone base station) Mean age: 38.2 y Female: 57%; 80 unexposed employees (working 2 km from the mobile phone base station) Mean age: 39.8 y Female: 59% (Participation rate not reported)	Excl.: epilepsy, psychiatric disorders, specific cause of headache	Prevalence of headache, irritability, memory changes, tremors, dizziness, blurred vision, depressive symptoms	Two sites with different distances to a mobile phone base station; Frequency band not reported, no meaningful exposure measurements	Chi-square test, student's t-test, ANCOVA; age, sex, occupation, education level, smoking and mobile phone use	Exposed vs. unexposed: Headache: OR=2.8 (1.1; 7.4) Memory changes: OR=7.5 (2.3; 27.0) Dizziness: OR=4.4 (1.3; 16.5) Depressive symptoms: OR=2.8 (1.0; 8.0) Blurred vision: OR=1.6 (0.7; 3.9) Sleep disturbances: OR=2.8 (1.1; 7.4) Irritability: OR=1.5 (0.7; 3.3) Lack of concentration: OR=1.8 (0.7; 5.0)
Heinrich 2007	Field intervention	95 employees of an office building in Bavaria (Germany) Median age 40 y (range: 26-62 y) Female: 30% (Participation rate: ca. 32%)	Not mentioned	Questionnaire with 21 symptoms: difference of the score between evening and morning	UMTS base station on the roof of the building randomly turned on/off during 1-3 consecutive days over a period of 70 days[1] E-field during exposure: maximum 0.53 V/m, mean 0.1 V/m	models with autocorrelation; gender, air pressure, day of week, self reported EHS and ability to perceive EMF	During exposure non-significant increase of symptom score (p=0.08). Cumulative exposure was not associated with symptom score (p=0.42)

Web table 6-2 (continued)

Refer-ence	Study design	Study collective (participation rate)	Inclusion/exclusion criteria	Outcome	Exposure assess-ment	Statistical models; covariables	Results
Danker-Hopfe 2008	Field inter-vention	397 individuals of 10 German towns with no mobile phone cover-age, only weak other RF-EMF sources and no emotional public debate about base station setting Mean age: 45 y Female: 51% (Participation rate: 17%)	Incl.: place of residence <500m from a base sta-tion, age >17 y	Sleep diary and polysom-nography	Transmission of GSM 900/GSM 1800 base station during 5 con-secutive nights on or off Randomized.[1] E-field during expo-sure: 1 mV/m to 6 V/m, mean: ca. 0.1 V/m	Student's t-test or Wlil-coxon test	Exposed vs. unexposed: Sleep efficiency (p=0.84) Time spent in bed (p=0.29) Total sleep time (p=0.39) Sleep latency (p=0.83) Wake after sleep onset (p=0.88) Restfulness (p=0.59)
Leitgeb 2008	Cross-sectional	43 EHS volunteers from Germany and Austria recruited by press release Mean age: 56 y Female: 61% (Participation rate: 44%)	Incl.: EHS, Pittsburgh index >5 Excl: neurological and psychological disorders, somatic reasons for sleep disorders, drug consumption, medical treatment	Written ques-tionnaire on subjective sleep quality	3 control nights with-out shield If unshielded: typical measured levels <0.5% ICNIRP limit, maximum level: 3.5% of ICNIRP limit[2]	Linear regression	Non-significant improvement of sleep score with increasing GSM-EMF at baseline (p>0.05)
	Field inter-vention			Polysomno-graphy	3 control nights with-out shield, 3 nights with sham shield and 3 nights with true shield Randomized, single-blind	MANOVA, Kolmogorov-Smirnov-Z test or Mann-Whithey-U test	3 participants with improvement by true shield 6 participants with placebo effects (improvement by true and sham shield compared to control nights) 34 volunteers with no effects
							2 participants with improvement by true shield 6 participants with sleep impairment by true shield 5 participants with mixed effects 1 participant with placebo effects 29 volunteers with no effects
Thomas 2008	Field inter-vention	329 randomly selected residents of 4 German towns Age range: 18-65 y Female: 53% (Participation rate: 30%)	Incl.: age 18-65 y	Selection of items from Freiburger Beschwerde-liste: occur-rence of symp-tom at least twice per month	Personal dosimetry of total RF-EMF[3] during waking hours of one day (in % of ICNIRP limit) Lowest quartile (ref-erence): <0.15% of ICNIRP limit Top quartile: 0.21 to 0.58% of ICNIRP limit[4]	Logistic regression; age, gender	Top quartile vs. reference: Headache: OR=1.2 (0.2; 6.4) Neurological symptoms: OR=0.6 (0.1; 4.2) Cardiovascular symptoms: OR=2.4 (0.6; 9.9) Sleeping disorders: OR=1.1 (0.5; 2.1) Fatigue: OR=0.7 (0.3; 1.8)
	Longitu-dinal			Selection of items from the Zerssen symp-tom list: at least moderate symp-tom intensity			Morning/afternoon: Headache: OR=0.6 (0.1; 2.8) / 3.1 (0.8; 12.6) Neurol. sympt.: OR=0.5 (0.2; 1.3) / 0.4 (0.2; 1.2) Fatigue: OR=0.5 (0.2; 1.1) / 0.5 (0.3; 1.0) Concentr. probl: OR=0.3 (0.1; 1.8) / 1.4 (0.4; 4.7)

Web table 6-2 (continued)

Reference	Study design	Study collective (participation rate)	Inclusion/exclusion criteria	Outcome	Exposure assessment	Statistical models; covariables	Results
Auger 2009	Field intervention	57 volunteers; Mean age: 40.7 y, Female: 61%	Not mentioned	Standardized questionnaire on well-being (MDBF) with 3 scales: mood, alertness, calmness	In a "field laboratory" three exposure levels were created by shielding devices (5*50min): Low=0.04 V/m; medium=0.24 V/m; high=0.90 V/m. Exposure originated predominantly from a GSM 900 antenna	ANOVA; age, gender and degree of possible EHS	scenarios with high and medium exposure compared to low exposure. No effects for "good mood" and "alertness".
Berg-Beckhoff 2009	Cross-sectional	1326 individuals from 8 urban German regions Age range: 15-71 y Female: 51% (Partipation rate: 21%)	Participants of the panel survey by Blettner 2009	5 symptom scales: sleep quality (PSQI), headache (HIT-6), symptom score (Zerssen list), SF-36	UMTS from a spot measurement in the bedroom Dichotomized at 90th percentile (i.e. >0.1 V/m)	Linear regression model; age gender, rural/urban, education level, mobile phone use, risk perception and stress	Score difference between highly and lowly exposed (95%-CI): PSQI: -0.15 (-0.69; 0.38) HIT-6: -0.24 (-1.57; 1.08) Zerssen: 0.55 (-1.05; 2.15) SF-36, physical: -0.14 (-1.80; 1.51) SF-36, mental: 0.37 (-0.93; 1.68)
Blettner 2009	Cross-sectional	26,039 German residents of a panel survey that is regularly carried out Age range: 14-69 y Female: 52% (Participation rate: 58.6%)	Not mentioned	Frick symptom score	Geo-coded distance to the closest mobile phone base station	Multiple linear regression model; age, gender, income, education, region, city inhabitants and concerns/attribution	CI): 0.34 (0.32; 0.37) Worries were associated with self-reported distance but not with objectively geo-coded distance.
Kühnlein 2009	Cross-sectioanl	1433 randomly selected children of 4 German towns Age range: 8-12 y (Participation rate: 53%)	Incl.: age 8-12 y, German nationality, only 1 participant from 1 household	Computer assisted personal interview (CAPI): questions on chronic symptoms during the last 6 months	EMF[3] over 24h (in % of ICNIRP limit) Mean exposure dichotomized at 90th percentile (value of cut-off not reported)	Multiple logistic regression models; age, sex, parents' level of education, parents' environmental worries, mobile phone use, DECT use, estimated distance to next mobile phone base station and study site	> 90^{th} percentile vs. < 90^{th} percentile: Headache: OR=0.6 (0.3; 1.0) Irritation: OR=1.0 (0.6; 1.5) Nervousness: OR=0.8 (0.5; 1.4) Dizziness: OR=1.1 (0.5; 2.4) Fear: OR=0.6 (0.2; 2.0) Sleeping problems: OR=1.0 (0.6; 1.5) Fatigue: OR=0.8 (0.6; 1.3)

Footnotes:
[1] Transmission status of base station was not detectable by mobile phone; [2] 3.5 % of ICNIRP limit corresponds to 2 V/m at a frequency of 1800 MHz; [3] Total RF-EMF: sum of GSM 900, GSM 1800, UMTS (up- and downlink), DECT and WLAN; [4] 0.21% of ICNIRP limit corresponds to 0.123 V/m at a frequency of 1800 MHz

Abbreviations:
ANCOVA: Analysis of covariance; DECT: Digital Enhanced Cordless Telecommunications; EMF: Electromagnetic field; EHS: Electromagnetic hypersensitivity; GSM: Global System for Mobile Communications; HIT-6: Hedache Impact Test; ICNIRP: International Commission on Non-Ionizing Radiation Protection; PSQI: Pittsburgh Sleep Quality Index; UMTS: Universal Mobile Telecommunications System WLAN: Wireless Local Area Network

Web table 6-3: Risk of various types of bias in the included studies classified into the categories low, medium and high. For medium and high risks of bias, the direction is indicated with arrows: ↓ refers to an underestimation of the exposure effect association (false negative); ↑ refers to an overestimation of the association (false positive) and ↕ indicates that the direction of the bias is not clear.

Note that blinding was also assessed: all randomized human laboratory trials were double blind. In field intervention studies and in observational epidemiological studies, it is impossible to ensure blinding regarding exposure.

Study	Exposure assessment bias	Selection bias	Randomisation bias	Confounding	Other bias
Randomized human laboratory trials					
Hinrichs 2005	low	low	low	↕medium: sequence of exposure not considered	↓medium: low statistical power (n=13)
Regel 2006	low	low	low	low	no
Eltiti 2007	low	low	↑high: exposure conditions were not counterbalanced	↑medium: sequence of exposure not considered	↓ medium : conservative multiple endpoint adjustment (Bonferroni)
Riddervold 2008	low	↑medium: unequal headache score at baseline of various exposure conditions	low	low	↕ medium: selective reporting: only results from one out of three exposure conditions reported
Furubayashi 2009	low	low	low	low	↓medium: low statistical power for EHS analysis (n=11)
Field intervention epidemiological studies					
Heinrich 2007	↓medium: small exposure contrasts and no individual exposure assessment	low	low	low	no
Danker-Hopfe 2008	↓medium: small exposure contrasts and no individual exposure assessment	low	low	↕medium: sequence of exposure not considered	↓medium: data analyses based on weekly average instead of single nights
Leitgeb 2008	↓medium: small exposure differences, no individual exposure assessment	low	low	↑high: day of week not considered	↕medium: only individual based data analysis, no comparison of group averages
Augner 2009	low	↑medium: unclear criteria for combining the results from various exposure conditions	low	↑high: only adjusted for age	↕medium: small control group (n=9)

Study	Exposure assessment bias	Selection bias	Randomisation bias	Confounding	Other bias
Observational epidemiological studies					
Hutter 2006	↓medium: small exposure contrasts	↑medium: affected people close to base station may be more likely to participate	low	low	↑no multiple endpoint correction
Maes, 2006	↕medium: no exposure measurements	low	low	↕medium: only few confounders tested (results not shown)	no
Meyer, 2006	↓high: crude exposure assessment	low	low	↕medium: only age and gender considered	↓medium: small number of cases
Abdel-Rassoul 2007	↑high: crude exposure assessment, no measurements	↕high: unclear how participants were recruited and selected; workers are compared with general population	↑high: participants must be aware of their exposure status	↕medium: only few confounders considered	no
Thomas 2008	↓medium: small exposure contrasts ↕medium: no differentiation between base station and handset exposure ↑medium: personal measurements might be manipulated	↑medium: affected people who are highly exposed may be more likely to participate	low	↕medium: only age and gender considered	no
Berg-Beckhoff 2009	↓medium: small exposure contrasts	↑medium: agreeing to participation in the measurement study may not be random	low	low	no
Blettner 2009	↕high: crude exposure assessment	↑medium: affected people living close to base station may be more likely to participate	↑medium: people may be aware about distance to closest MPBS	low	no
Kühnlein 2009	↓medium: small exposure contrasts ↕medium: no differentiation between base station and handset exposure ↑medium: personal measurements might be manipulated	↑medium: affected people who are highly exposed may be more likely to participate	low	low	no

Article 8: Effects of everyday radio frequency electromagnetic field exposure on sleep quality: a cross-sectional study

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Effects of Everyday Radiofrequency Electromagnetic-Field Exposure on Sleep Quality: A Cross-Sectional Study

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Mohler, E., Frei, P., Braun-Fahrländer, C., Fröhlich, J., Neubauer, G. and Röösli, M. Effects of Everyday Radiofrequency Electromagnetic-Field Exposure on Sleep Quality: A Cross-Sectional Study.

The aim of this cross-sectional study was to investigate the association between exposure to various sources of radiofrequency electromagnetic fields (RF EMFs) in the everyday environment and sleep quality, which is a common public health concern. We assessed self-reported sleep disturbances and daytime sleepiness in a random population sample of 1,375 inhabitants from the area of Basel, Switzerland. Exposure to environmental far-field RF EMFs was predicted for each individual using a prediction model that had been developed and validated previously. Self-reported cordless and mobile phone use as well as objective mobile phone operator data for the previous 6 months were also considered in the analyses. In multivariable regression models, adjusted for relevant confounders, no associations between environmental far-field RF EMF exposure and sleep disturbances or excessive daytime sleepiness were observed. The 10% most exposed participants had an estimated risk for sleep disturbances of 1.11 (95% CI: 0.50 to 2.44) and for excessive daytime sleepiness of 0.58 (95% CI: 0.31 to 1.05). Neither mobile phone use nor cordless phone use was associated with decreased sleep quality. The results of this large cross-sectional study did not indicate an impairment of subjective sleep quality due to exposure from various sources of RF EMFs in everyday life

INTRODUCTION

The possible effects of radiofrequency electromagnetic-field (RF EMF) exposure on health-related quality of life are of public health concern (*1–3*). The most often reported complaints related to RF EMFs are impairments of sleep quality (*4, 5*).

Several studies investigated the effect of short-term RF EMF exposure on sleep measures in a laboratory setting, applying real and sham exposure randomly under well-controlled exposure conditions (*6–8*). Objective sleep measures derived from electroencephalography (EEG) were used in these laboratory studies. Overall, these studies showed no consistent association between RF EMF exposure and objective sleep measures (i.e. sleep architecture), but small differences for different frequency ranges in the EEG were observed repeatedly after exposure to RF EMFs. The primary aim of laboratory studies is to identify a possible biological mechanism of the effect of RF EMF exposure on sleep, if any exists. In general, laboratory studies are conducted with a relatively small number of participants and therefore have limited statistical power to investigate subjective sleep quality. Moreover, the unfamiliar environment of a sleep laboratory may prevent detection of subtle effects of RF EMFs on sleep quality, as has been reported by several individuals.

Epidemiological studies allow the examination of the association between RF EMFs and subjective sleep quality in a large population sample. The main challenge is to perform an appropriate exposure assessment. Until now, only a few studies were conducted. In early studies, associations between RF EMF exposure and subjective well-being or sleep quality were observed (*9, 10*). However, in these studies, simple exposure proxies like self-reported distance to mobile phone base stations were used, which have been demonstrated to be inadequate (*11, 12*). Information bias was also of concern in these studies and might have influenced the results. Additionally, selection bias might affect results in such cross-sectional studies if participation is related to both health and exposure status (*13, 14*). More recent studies on RF EMF exposure and sleep quality used spot measurements in the bedroom for exposure classification (*15, 16*). No differences in sleep quality (Pittsburgh Sleep Quality Index) or in other health outcomes (headache, SF-36 and health complaint list) were observed between individuals with high and low exposures. Although more sophisticated exposure assessment methods were used in these studies, it still is not

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clear how well such spot measurements represent long-term exposure to various sources of RF EMFs in our everyday environment. For these reasons, in our study, we used personal RF EMF exposure measurements and modeling of fixed-site transmitters (e.g. mobile phone base stations and broadcast transmitter) to develop a method to assess individual exposure (*17*).

Due to the unknown biological mechanism, it is unclear which aspect of exposure is relevant for sleep disturbances, if there are any. It is conceivable that exposure at the head, caused mainly by mobile and cordless phones, is most relevant (close to body sources). Alternatively, environmental sources like exposure from mobile phone base stations or broadcast transmitter, which in general cause lower but continuous whole-body exposures, might play a role (far-field environmental RF EMF exposure). RF EMF exposure might cause symptoms immediately, or the accumulated radiation might be more important. Additionally, psychological aspects appear to be important. Previous studies showed that subjective well-being and sleep quality can be impaired in people from concern or expectations if they think they are highly exposed to various sources of RF EMFs (*3*) (also called a nocebo effect).

The primary aim of this cross-sectional study was to evaluate whether environmental RF EMF exposure is associated with self-reported sleep quality. We also evaluated whether sleep quality is affected by other RF EMF exposure surrogates such as night exposure or use of mobile or cordless phones.

METHODS

In May 2008, 4000 questionnaires entitled "environment and health" were sent out to people aged between 30 to 60 years who were randomly selected from the population registries of the city of Basel (Switzerland) and from five communities in the surroundings of Basel. To minimize noneligibility due to language difficulties, only Swiss residents or people living in Switzerland for at least 5 years were selected. A reminder letter was sent out 3 weeks after the first invitation for participation. Nonresponders were contacted by phone 6 to 10 weeks after the first questionnaires were sent out, and they were asked a few key questions. Ethical approval for the study was received from the Ethical Commission of Basel on March 19, 2007 (EK: 38/07).

Written Questionnaire

The questionnaire addressed three issues: (*1*) sleep quality and general health status; (*2*) exposure-relevant characteristics and behaviors (*17*) such as owning a mobile phone, a cordless phone, and/or a wireless LAN and duration of cordless phone use and mobile phone use; and (*3*) socio-demographic factors such as age, gender, education, marital status and additional confounders like body mass index (BMI), physical activity, smoking behaviors and alcohol consumption.

Excessive Daytime Sleepiness and Self-Reported Sleep Disturbances

To assess subjective sleep quality, we used two sleep outcomes. Daytime sleepiness was determined by the Epworth Sleepiness Scale (ESS), which assigns values ranging from 0 (no daytime sleepiness) to 21 (very excessive daytime sleepiness) (*18*). We calculated the ESS scores and created a new binary variable according to a previous study on insomnia indicating excessive daytime sleepiness (ESS score over 10) (*19*).

General subjective sleep quality was assessed by using four standardized questions from the Swiss Health Survey 2007 (*20*). The four questions on subjective sleep quality in the Swiss Health Survey asked about the frequency of difficulty in falling asleep, fitful sleep, waking phases during night, and waking too early in the morning using a four-point Likert scale with categories "never", "rare", "sometimes" and "most of the time". Out of these four questions, a binary sleep quality score (SQS) was calculated by adding up all items (ranging from 0 to 12) and defining a score of eight as having sleep disturbances (*20*).

Exposure Assessment

Our main hypothesis was that environmental whole-body exposure in everyday life may affect sleep quality. We developed a model for predicting personal exposure to environmental RF EMFs on the power flux density scale in mw/m^2 (*17*) in which we measured personal RF EMF exposure of 166 volunteers from our study area by means of a portable EME Spy 120 exposure meter. Volunteers carried the exposimeter and filled in an activity diary for 1 week (*21*). The exposimeter measured 12 different frequency bands of RF EMFs ranging from FM radio (frequency modulation; 88–108 MHz), TV (television, 174–223 MHz and 470–830 MHz), Tetrapol (terrestrial trunked radio police; 380–400 MHz), uplink in three frequency ranges (communication from mobile phone handset to base station; 880–915, 1710–1785, 1920–1980 MHz), downlink in three frequency ranges (communication from mobile phone base station to handset; 925–960, 1805–1880, 2110–2170 MHz), DECT (digital enhanced cordless telecommunications; 1880–1900 MHz), and W-LAN (wireless local area network; 2400–2500 MHz). In addition, we developed a three-dimensional geospatial propagation model in which the average RF EMF from fixed-site transmitters (e.g., mobile phone base stations and broadcast transmitters) was modeled for the study region (in- and outside of buildings) (*22, 23*). Based on this geospatial propagation model and on data from the exposimeter measurements, the relevance of potential predictors on exposure was examined in multivariable non-linear regression models. The following exposure-relevant factors were identified and included in the prediction model for environmental exposure in everyday life (*17*): owning a mobile phone, owning a wireless LAN at home, having the DECT base station in the bedroom, having a cordless phone at the place where one spends the most of their time during the day, house characteristics (window frame and type of house wall), hours per week in public transport and cars, percentage full-time equivalent spent at an external workplace, and exposure from fixed-site transmitters at home computed by the geospatial propagation model (*22, 23*).

To estimate exposure during the night, a separate night prediction model was developed. Ownership of a cordless phone base station in the bedroom, wireless LAN in the bedroom, house characteristics (type of house wall and window frame), and the modeled value of fixed-site transmitters were included in this specific prediction model.

We used the above-mentioned geospatial propagation model for modeling exposure from fixed-site transmitters at home (*22*) in mW/m^2 as well as in percentage of the ICNIRP (International Commission on Non-Ionizing Radiation Protection) (*24*) reference level according to method of Thomas *et al.* (*28*).

Finally, with respect to local exposure to the head, we used self-reported use of mobile and cordless phones per week as reported in the written questionnaire. Informed consent was also sought from participants to obtain operator data for their mobile phone use for the last 6 months from the three Swiss mobile phone network operators.

Sensitivity Analysis

To evaluate a nocebo effect and information bias (which is also of concern in this area of research), we asked participants about their subjective exposure. They had to estimate their exposure compared to the Swiss population and to indicate whether they felt they were equally, less or more exposed in comparison to the average of the Swiss population. Geo-coded data were available for all study participants. This allowed us to calculate the distance from their residence to the next mobile phone base station as an additional exposure surrogate.

Nonresponder Analyses

To evaluate the extent of potential selection bias in our study, nonresponder interviews were conducted to gather information on general health status, socio-demographic factors and exposure-relevant behaviors and factors. One month after the reminder letter was sent out, we tried to contact all nonresponders. Information on age, gender and geo-coded addresses was available for all 4000 persons.

We calculated "selection bias factors" for different exposure proxies (i.e., owning a mobile phone, a cordless phone and/or a W-LAN and distance to the next mobile phone base station) using the Greenland method (*25*) as was done by Vrijheid *et al.* (*26*). For these calculations we assumed that data from nonresponder phone interviews are representative for all nonresponders. Dividing the observed odds ratio by the bias factor yields the correct unbiased association between exposure and outcome. A bias factor of 1.0 indicates that there is no bias.

Statistical Analyses

For binary outcomes (ESS score and SQS), logistic regression models with three groups of exposure levels for all exposure proxies (<50th percentile, 50th to 90th percentile, >90th percentile) were performed. Mean average RF EMF exposures were calculated in mW/m^2 and converted to V/m. In addition, linear regression models were computed using the continuous score of both sleep scales. Separate analyses were done for each of the four questions of the Swiss Health Survey.

The models were adjusted for age, sex, body mass index (BMI), stress perception, physical activity, smoking habits, alcohol consumption, self-reported disturbance due to noise, living in urban or suburban areas, belief in health effects due to RF EMF exposure, education and marital status. Use of mobile and cordless phones was included in all models as an independent exposure measure. Missing values in the confounder variables were replaced with values of either the most common category (categorical variables) or with the mean value (linear variables) to ensure that all analyses were performed with an identical data set for the ESS and the SQS, respectively. Most missing values in confounder variables were observed in self-reported disturbance of noise [33 missing out of 1212 observations (2.7%)]. Stratified analyses and testing for interaction were done for people reporting as electrohypersensitive (EHS). We defined EHS individuals as those reporting as "electrohypersensitive" or those reporting adverse effects due to RF EMFs.

All statistical analyses were carried out using STATA 10.1 (StataCorp, College Station, TX).

RESULTS

Study Participants

Of the 4000 persons participating in the study, 237 were excluded due to noneligibility because of severe disabilities (n = 27), death (n = 1), incorrect addresses (n = 36), absence during study time (n = 73), or language problems (n = 100). A total of 1375 people completed the questionnaire. Detailed information on the response rate is illustrated in Fig. 1. Users of sleeping pills (n = 81) as well as night shift workers (n = 82) were excluded from all the analyses. The final analyses thus included 1212 participants. Due to missing values in exposure variables (mobile phone and cordless phone use) and in sleep quality scores (ESS and SQS), 1129 study participants remained for the analyses of excessive daytime sleepiness and 1163 study participants remained for the analyses of self-reported sleep disturbances. Characteristics of all study participants are listed in Table 1. The mean age (standard deviation) of study participants was 46 (*9*) years, and 39% of all responders lived in the city of Basel. There were more female (58%) than male participants. Ninety percent reported that they had a good or very good health status, which was comparable to the general Swiss population (87%).[2] The majority was married (60%) and of normal weight (BMI <25) (62%).

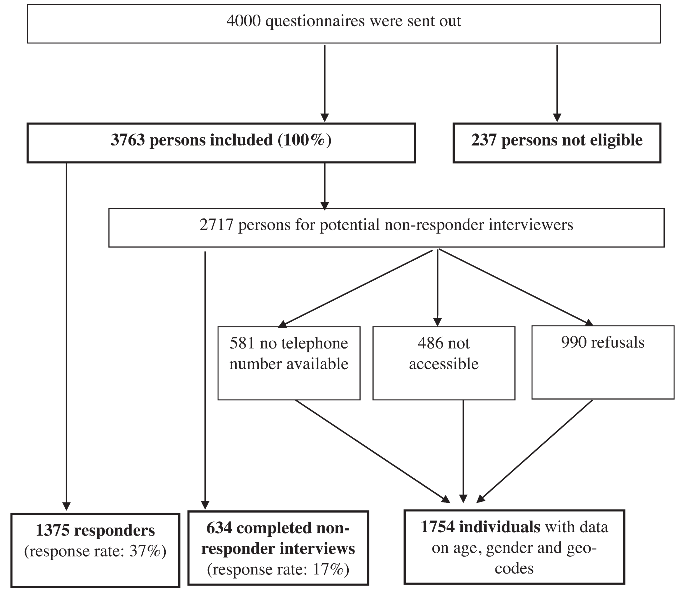

FIG. 1. Schematic illustration of the study design and response rate.

Seventy-eight percent of the study participants reported that they believed that there are people who develop adverse health effects due to RF EMF exposure, 18.2% assigned their own adverse health effects as being due to RE EMF exposure, and 8.1% reported that they were "electrohypersensitive". Due to overlapping, 20.9% of our study population was electrohypersensitive according to our definition.

[2] National Statistical Institute (Switzerland) 2007; http://www.bfs.admin.ch/bfs/portal/de/index/themen/14/02/01/key/01.html.

TABLE 1
Characteristics and Results of Statistical Comparison of all Study Participants (including nonresponders)

	Participants (n = 1212)[a]	*Percent*	Nonresponders (n = 2388)	*Percent*	P value
Age (years)					0.05
30–40	319	*26*	719	*30*	
41–50	421	*35*	829	*35*	
51–60	472	*39*	840	*35*	
Sex					<0.05
Female	706	*58*	1190	*50*	
Male	506	*42*	1198	*50*	
Distance to the next mobile phone base station (percentage closer than 50 m)	45	*4*	165	*7*	<0.05
Health status[b,c]					<0.05
Very good	445	*37*	215	*34*	
Good	636	*53*	302	*48*	
Half-half	107	*9*	86	*14*	
Bad	12	*1*	18	*3*	
Very bad	3	*0*	8	*1*	
Educational level[b,c]					0.171
None	79	*7*	56	*9*	
Apprenticeship	591	*49*	320	*51*	
Higher education/University	542	*45*	255	*40*	
Owning a mobile phone[b,c]					<0.05
Yes	1049	*87*	572	*90*	
No	163	*13*	60	*10*	
Owning a cordless phone[b,c]					0.176
Yes	994	*82*	537	*85*	
No	213	*18*	96	*15*	
Owning wireless LAN[b,c]					0.931
Yes	492	*41*	259	*41*	
No	709	*59*	370	*59*	

[a] After exclusion of nightshift workers (n = 82) and users of sleeping drugs (n = 81).
[b] Nonresponder data only for a subsample of 634 nonresponders who answered a short nonresponder interview by phone (numbers in nonresponder analyses can vary due to missing data).
[c] Data may not sum up to 100% due to missing data.

Level of Exposure

The predicted everyday life mean and median exposure was 0.18 V/m for all the included study participants. The cut-off point for 90th percentile was 0.21 V/m. The maximum predicted value was 0.33 V/m. The mean predicted exposure during the night was 0.06 V/m (median: 0.02 V/m, cut-off 90th percentile: 0.09 V/m, maximum: 0.33 V/m), and the mean exposure through fixed-site transmitters (geospatial propagation model) was 0.08 V/m (median: 0.04 V/m, cut-off 90th percentile: 0.12 V/m, maximum: 0.62 V/m). The mean level of exposure from fixed-site transmitters was 0.15% of the ICNIRP reference level. On average, study participants reported using their mobile phones 62.8 min per week and their cordless phones 75.1 min per week. Informed consent for objective data on mobile phone use from the network operators was obtained from 470 study participants. Those who gave informed consent reported that they used their mobile phone 46.5 min per week, while the operator data showed a mobile phone use of 28.8 min per week (*27*). The Spearman rank correlation was 0.76 (95% CI: 0.71–0.83) for self-reported mobile phone use and the operator data.

The majority (64%) of the participants estimated that their exposure was similar to the average for the Swiss population, while 29% believed they were less exposed and 7% believed they were more exposed.

Excessive Daytime Sleepiness (ESS score)

The prevalence of excessive daytime sleepiness (ESS score > 10) was 29.5%. the results of the logistic regression models for crude and adjusted odds ratios (OR) are presented in Table 2. No statistically significant association between excessive daytime sleepiness and various exposure surrogates was observed. The analysis showed a tendency toward excessive daytime sleepiness for the highest-exposed group through fixed-site transmitters, although it was not statistically significant. This finding was confirmed when exposure

TABLE 2
Association between Excessive Daytime Sleepiness (Epworth Sleepiness Scale) and Different Exposure Surrogates [odds ratios (OR) and 95% CI of the three exposure categories]

	Exposure categories							
	< 50th percentile		50th–90th percentile			> 90th percentile		
Excessive daytime sleepiness (n = 1129)	No. of cases[a]	OR	No. of cases[a]	OR	95% CI	No. of cases[a]	OR	95% CI
Far-field exposure								
Everyday life exposure								
Crude	180	1.00	153	1.10	(0.84–1.43)	25	0.77	(0.47–1.24)
Adjusted[b]	180	1.00	153	1.14	(0.83–1.57)	25	0.58	(0.31–1.05)
Exposure during night								
Crude	174	1.00	149	1.14	(0.87–1.48)	35	1.06	(0.68–1.65)
Adjusted[b]	174	1.00	149	1.05	(0.76–1.43)	35	1.21	(0.74–1.98)
Exposure through fixed-site transmitters								
Crude	170	1.00	142	1.07	(0.82–1.40)	46	1.86	(1.21–2.85)
Adjusted[b]	170	1.00	142	1.02	(0.74–1.39)	46	1.52	(0.93–2.50)
Close-to-body exposure								
Mobile phone use (self-reported)								
Crude	210	1.00	106	1.18	(0.89–1.57)	32	1.05	(0.69–1.64)
Adjusted[b]	210	1.00	106	1.24	(0.91–1.70)	32	1.03	(0.62–1.69)
Mobile phone use (operator data)[c]								
Crude	65	1.00	152	1.11	(0.72–1.70)	14	1.26	(0.63–2.54)
Adjusted[b]	65	1.00	152	1.30	(0.82–2.07)	14	0.91	(0.39–2.11)
Cordless phone use (self-reported)								
Crude	178	1.00	165	1.27	(0.98–1.65)	13	1.44	(0.71–2.90)
Adjusted[b]	178	1.00	165	1.30	(0.99–1.72)	13	1.65	(0.72–3.50)

[a] Indicates number of people in the corresponding exposure group with an Epworth sleepiness score over 10.
[b] Adjusted for age, body mass index, sex, physical activity, alcohol consumption, smoking habits, stress perception, urban/suburban, marital status, educational level, noise perception, belief in health effects due to radiofrequency electromagnetic-field exposure.
[c] For a subsample of 453 subjects who consented to obtain data from the operator.

was calculated as a percentage of the ICNIRP reference level (adjusted OR for the 90th percentile: 1.62; 95% CI: 0.99–2.64). This finding was confirmed when exposure was calculated as a percentage of the ICNIRP reference level (adjusted OR for the 90th percentile: 1.62; 95% CI: 0.99–2.64). Similar results were found for linear regression models (data not shown).

Based on interaction tests, we found no indication that RF EMF exposure affects EHS individuals differently than non-EHS individuals ($P > 0.05$ for all exposure surrogates).

Self-Reported Sleep Disturbances (SQS)

Problematic sleep disturbances were reported by 9.8% of respondents. There was no evidence that having sleep disturbances was influenced by everyday life exposure, exposure through fixed-site transmitters or exposure during the night (Table 3). The OR for the top decile of exposed individuals according to the percentage of the ICNIRP reference value was 0.95 (95% CI: 0.47 to 1.90). Mobile phone and cordless phone use showed no statistically significant effects on having sleep disturbances, but tendencies toward fewer sleep disturbances with increased use of a mobile phone could be seen in the logistic (Table 3) and linear regression models (data not shown). However, analysis of a subsample with objective mobile phone operator data did not show such a tendency (Table 3).

The separate analyses of each item on the sleep quality score (falling asleep, fitful sleep, waking phases during night, waking up early in the morning) revealed no exposure–response association (data not shown). Interaction tests and stratified analyses for EHS and non-EHS individuals showed no difference between the two subgroups.

Sensitivity Analysis

An association between self-reported sleep quality and self-estimated exposure could indicate the presence of information bias or a nocebo effect, or rather the development of symptoms due to concerns. In our study, we found some indications for the presence of a nocebo effect (Table 4). People reporting to be less exposed to mobile phone base stations in comparison to the average population are less likely to suffer from excessive daytime sleepiness (Table 4). Correspondingly, people who lived closer than 50 m to the closest mobile phone base station had a higher risk for excessive daytime sleepiness, although it was not statistically significant. Self-reported sleep disturbances were increased in people claiming to be more exposed in comparison to the average population. These trends were most pronounced

TABLE 3
Association between Self-Reported Sleep Disturbances (Sleep Quality Score) and Different Exposure Surrogates [odds ratios (OR) and 95% CI of the three exposure categories]

	Exposure categories							
	< 50th percentile		50th–90th percentile			> 90th percentile		
Self-reported sleep disturbances (n = 1163)	No. of cases[a]	OR	No. of cases[a]	OR	95% CI	No. of cases[a]	OR	95% CI
Far-field exposure								
Everyday life exposure								
Crude	98	1.00	68	0.91	(0.65–1.28)	14	0.87	(0.48–1.60)
Adjusted[b]	98	1.00	68	1.11	(0.72–1.70)	14	1.11	(0.50–2.44)
Exposure during night								
Crude	88	1.00	76	1.14	(0.81–1.50)	16	1.01	(0.57–1.80)
Adjusted[b]	88	1.00	76	1.30	(0.85–1.98)	16	1.29	(0.66–2.53)
Exposure through fixed-site transmitters								
Crude	88	1.00	77	1.15	(0.82–1.62)	15	0.94	(0.52–1.69)
Adjusted[b]	88	1.00	77	1.16	(0.76–1.75)	15	1.09	(0.53–2.22)
Close-to-body exposure								
Mobile phone use (self-reported)								
Crude	124	1.00	41	0.71	(0.49–1.05)	13	0.71	(0.38–1.30)
Adjusted[b]	124	1.00	41	0.67	(0.43–1.02)	13	0.64	(0.31–1.28)
Mobile phone use (operator data)[c]								
Crude	42	1.00	30	0.91	(0.54–1.51)	5	0.60	(0.22–1.62)
Adjusted[b]	42	1.00	30	1.57	(0.89–2.78)	5	1.03	(0.32–3.30)
Cordless phone use (self-reported)								
Crude	102	1.00	66	0.80	(0.57–1.12)	8	1.51	(0.67–3.40)
Adjusted[b]	102	1.00	66	0.71	(0.49–1.03)	8	1.11	(0.44–2.78)

[a] Indicates number of people in the corresponding exposure group with a sleep quality score over 8.
[b] Adjusted for age, body mass index, sex, physical activity, alcohol consumption, smoking habits, stress perception, urban/suburban, marital status, educational level, noise perception, belief in health effects due to radiofrequency electromagnetic-field exposure.
[c] For a subsample of 453 subjects who consented to obtain data from the operator.

for self-estimated exposure to a mobile phone base station. Subjective exposure was not correlated to modeled mobile phone base station radiation (Spearman correlation coefficient: –0.01) or total everyday life exposure (Spearman correlation coefficient: 0.13).

Nonresponder Analysis

To evaluate a possible selection bias, we compared responders of the questionnaire with nonresponders. The nonresponder analyses, comparing all 1212 participants included in our analyses with the 2388 nonresponders, showed small differences between study participants and nonresponders (Table 1). Nonresponders were generally younger, and the participation rate for women was higher than for men. The distance between the closest mobile phone base station and place of residence was smaller for the responders. Some of the nonresponder information was available only for the nonresponders who participated in the telephone interviews (n = 634): Participants in these telephone interviews were more likely to be an owner of a mobile phone (90%) than full study participants (87%). Study participants who filled in the questionnaire were somewhat healthier than nonresponders. No difference was observed in educational level in owning a wireless LAN or cordless phone. The prevalence of nonresponders (telephone interviews) who reported that they were "electrohypersensitive" was 16%. In the full study only 8% answered yes to the corresponding question ($P < 0.0001$).

In our selection bias factor, we found a bias factor of 0.79 for owning a mobile phone, 0.70 for owning a cordless phone, 0.95 for owning a W-LAN, and 1.33 for living within 50 m from a mobile phone base station. Thus we expect that in our study the exposure–response association for mobile and cordless phone use tends to be biased downward whereas the exposure–response association for fixed-site transmitter tends to be biased upward.

DISCUSSION

The aim of this study was to investigate the association between various RF EMF exposure surrogates and self-reported sleep quality. Neither everyday-life environmental RF EMF exposure nor exposure during night through fixed-site transmitters or from mobile and cordless phones was associated with excessive daytime sleepiness or with having sleep disturbances. We found some indication for nocebo effects and information bias; this means that persons who assumed that they were exposed more than the average for the Swiss population reported that they suffered often, although not statistically significantly so,

TABLE 4
Sensitivity Analysis to Evaluate the Possible Extent of Information Bias and Nocebo Effect: Association between Sleep Quality (excessive daytime sleepiness and self-reported sleep disturbances) and Subjectiveô Exposure

	Excessive daytime sleepiness (n = 1129)							
	Subjective exposure categories							
	equal[a]		lower			higher		
	No. of cases[b]	OR	No. of cases[b]	OR	95% CI	No. of cases[b]	OR	95% CI
Subjective exposure to all sources								
Crude	239	1.00	96	0.80	(0.60–1.06)	23	0.87	(0.52–1.47)
Adjusted[c]	239	1.00	96	0.78	(0.56–1.09)	23	0.84	(0.41–1.71)
Subjective exposure to mobile phone base station								
Crude	243	1.00	85	0.71	(0.53–0.95)	30	0.98	(0.62–1.59)
Adjusted[c]	243	1.00	85	0.67	(0.48–0.95)	30	0.83	(0.44–1.59)
	Excessive daytime sleepiness (n = 1129)							
	>50 m					≤ 50 m		
	No. of cases[b]	OR				No. of cases[b]	OR	95% CI
Distance to mobile phone base station (geo-coded)								
Crude	340	1.00	-	-	-	18	1.90	(1.00–3.59)
Adjusted[c]	340	1.00	-	-	-	18	2.06	(0.96–4.41)

[a] Reference group includes also "don't know" and missing values.
[b] Indicates number of people in the corresponding exposure group with an Epworth sleepiness score over 10 or a sleep quality score over 8, respectively.
[c] Adjusted for age, body mass index, sex, physical activity, alcohol consumption, smoking habits, stress perception, urban/suburban, marital status, educational level, noise perception, believe in health effects due to radiofrequency electromagnetic-field exposure.

from sleep disturbances than participants who felt that they were equally exposed as the average of the Swiss population.

Strengths

Our study is based on a large sample size. To our knowledge, our study used the most comprehensive exposure assessment method to date by considering exposure-relevant behavior and characteristics (prediction model) as well as modeling RF EMFs from fixed-site transmitters with a geospatial model (*22*). All relevant exposure sources of everyday life were included in the prediction model, and the feasibility and reproducibility of this exposure assessment method could be demonstrated (*17*). Using prediction models for exposure assessment instead of conducting spot or personal measurements, as has been done in other studies (*15, 16, 28*), is time- and cost-saving for large study populations and is expected to better represent all sources of RF EMF exposure in everyday life.

We included several exposure surrogates in our study. This allowed us to check for consistency and biological plausibility, because no biological mechanism has been established. In particular, we included both close-to-body sources and far-field sources. In addition to self-reported mobile phone use, we considered objective operator data on mobile phone use for a subsample who gave consent.

Limitations

The cross-sectional study design is one of our main limitations, in particular with respect to EHS individuals. EHS individuals may tend to avoid known sources of RF EMF exposure and are therefore expected to be less exposed. If so, a cross-sectional study, where outcome and exposure are measured at the same time, could not capture an increased risk. It could even result in observation of a protective effect from exposure (although this was not the case in our study). Conversely, people who did not attribute their own symptoms to EMF exposure were not expected to avoid exposure sources. Thus our cross-sectional study should reveal an association in nonhypersensitive individuals, if one is present, because RF EMF exposure is relatively constant over a few months (*21*). This means that present exposure is also representative of exposure a few months before. In this regard, it is also relevant that self-estimated exposure actually is not correlated to true exposure. This indicates that most persons are not aware of their most relevant exposure sources. Unawareness of the exposure status implies that information bias is unlikely in our study.

In our study, we did not take polysomnographic sleep measures. We were mainly interested in self-reported data on sleep quality and well-being, because a decrease in self-perceived sleep quality due to RF EMF exposure is the most often stated concern of the population (*3, 5*).

TABLE 4
Extended

Self-reported sleep disturbances (n = 1163)							
Subjective exposure categories							
equal[a]		lower			higher		
No. of cases[b]	OR	No. of cases[b]	OR	95% CI	No. of cases[b]	OR	95% CI
116	1.00	49	0.92	(0.64–1.32)	15	1.23	(0.67–2.27)
116	1.00	49	1.05	(0.68–1.64)	15	1.47	(0.62–3.49)
109	1.00	47	1.08	(0.74–1.56)	24	1.99	(1.20–3.30)
109	1.00	47	1.16	(0.74–1.82)	24	1.61	(0.76–3.43)
Self-reported sleep disturbances (n = 1163)							
>50 m					≤ 50 m		
No. of cases[b]	OR				No. of cases[b]	OR	95% CI
171	1.00	-	-	-	9	1.53	(0.72–3.25)
171	1.00	-	-	-	9	1.13	(0.41–3.04)

Subjectively perceived sleep quality is relevant to health because it is an established factor that influences personal well-being (*29*). Collecting more sophisticated sleep measures using electroencephalography (EEG) would require considerable additional effort in this large study population, and such an unfamiliar measurement procedure could mask subtle effects on self-perceived sleep quality.

The participation rate for the full study (whole questionnaire data) was 37% and was therefore lower than we had expected and lower than in the study of Kühnlein *et al.* (*30*) and similar to that of Thomas *et al.* (*28*). In recent years, a decreasing response rate has been a commonly observed phenomenon in epidemiological research (*31*). In our study people might have declined because we asked them to give their informed consent to provide objective data about their mobile phone use from the mobile phone operator companies. People may have felt that it was an invasion of their privacy. The main concern in having a low participation rate is selection bias. We made considerable effort to evaluate potential bias from nonparticipation. To be able to assess the risk of selection bias, we performed nonresponder interviews, and data on age, gender and geo-codes were available for all 4000 persons. We were concerned that people attributing their sleep disturbances to mobile phone base stations or to RF EMFs in general would be more motivated to participate in our survey (*32, 33*). If these people live closer to a mobile phone base station than the average population, this could result in a bias, because distance is one parameter of our exposure prediction model. Interestingly, we found indications of the opposite but yielding the same possible bias: Study participants generally were healthier than nonresponders, and the proportion of persons living close to a mobile phone base station (<50 m) was smaller for participants than nonparticipants. Thus our selection bias modeling yielded a selection bias factor of 1.33 for living within 50 m of a mobile phone base station. According to this selection bias modeling our observed exposure–response associations for fixed site transmitter may be biased upward. Conversely, our exposure–response associations for mobile and cordless phone use may be biased downward.

Interpretation

The prevalence of excessive daytime sleepiness in our study was similar to previous studies in which 32.4% reported suffering from excessive daytime sleepiness (*34*). Prevalence of sleep disturbances was in our study even lower (9.8%) than observed in a study of a Swiss working population (*20*), where 19% of a relatively young Swiss working population suffered from disorders of initiating and maintaining sleep.

We found no consistent evidence that RF EMF exposure is associated with subjective sleep quality. Our findings contradict early studies that used self-estimated distance to mobile phone base stations as exposure proxy (*9, 10*). This approach has been shown to be inappropriate for exposure estimation (*12, 14, 35*). Moreover, these early studies without objective exposure measures are likely to be affected by nocebo effects since we found some indication for such a bias in our study when using self-estimated exposure measures that were poorly correlated to true exposure levels. This was particularly pronounced with respect to self-estimated mobile phone base station radiation.

Our prediction models are developed and validated on the power flux density scale (mW/m^2). In our prediction model for everyday life exposure, we added up contributions from different sources on the power flux density scale, based on the assumption that effects are not dependent on frequency. It has also been speculated in other studies that effects in the low-dose range maybe dependent on frequency, and another study weighted the exposure contributions according to the ICNIRP reference level (*28*). However, for exposure from a fixed-site transmitter, where we were able to compare both scales, we found a very high correlation (Spearman = 0.96), and the results of the epidemiological analyses were similar. This suggests that choice of the exposure scale is not crucial unless the effect is very frequency specific.

Our findings are in line with more recent cross-sectional studies on subjective sleep quality that used spot measurements in the bedroom for exposure assessment (*15, 16*). This is probably an acceptable exposure proxy for environmental RF EMF exposure during the night, but it does not capture exposure during the day or exposure to close-to-body sources that one might be exposed to prior to sleep. However, such exposure may be relevant: Several studies indicated that exposure to a mobile phone prior to sleep affects EEG during the night (*7, 8, 36, 37*).

In addition to the cross-sectional studies on self-reported sleep quality and RF EMF exposure at home, two studies investigated sleep behavior at home using an experimental approach and recording polysomnographic sleep measures. In a German study of 394 individuals living within 500 m of a mobile phone base station, polysomnographic measures were recorded during five consecutive nights. A transportable mobile phone base station (GSM 900 and 1800) was installed and randomly turned on and off.[3] Leitgeb *et al.* (*38*) recruited 43 volunteers who reported to be EHS. Polysomnography was applied during 9 nights (3 control nights, 3 nights with sham shielding, and 3 nights with true shielding). In both studies, polysomnographic measures were not related to exposure.

We evaluated various exposure proxies. Except in a subgroup analysis with non-sensitive individuals for excessive daytime sleepiness and cordless phone use, no statistically significant effects were found. Given the numerous tests performed, one statistically significant result can be expected by chance. Similarly, some of the observed exposure–response tendencies such as the decreased occurrence of sleep disturbances for the moderate user of cordless phones are probably due to chance or may be affected by selection bias. If there were a true exposure–response association in our large study population, we would have expected to see a consistent pattern in terms of outcome (i.e., similar effects for sleep quality or daytime sleepiness) or in terms of exposure sources (i.e., similar effects for close-to-body sources or for environmental sources). Nevertheless, the cross-sectional design is a limitation, particularly if one has the hypothesis that people avoid exposure if they are suffering from sleep disturbances. In our study we found no evidence for such a behavior, nor have recent reviews suggested that the ability to perceive RF EMF exposure actually exists (*14, 39*).

Overall, we found no indication that RF EMF exposure in our daily life impairs subjective sleep quality. In contrast to previous studies on that topic, we considered all relevant RF EMF sources of the everyday environment in our exposure assessment through consideration of various proxies that are relevant in everyday life.

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Article 9: Cohort study on the effects of radio frequency electromagnetic field exposure in everyday life on non-specific symptoms of ill health and tinnitus

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Abstract

Objective: To investigate the effect of exposure to radio frequency electromagnetic fields (RF-EMF), as produced by mobile phones and environmental far-field sources such as mobile phone base stations and broadcast transmitters, on the development of non-specific symptoms and tinnitus.

Design: Prospective cohort study.

Setting: City of Basel, Switzerland, and surrounding communities.

Participants: 1375 randomly selected participants aged 30-60. Participation rate at follow-up (one year after the baseline survey) was 82%.

Main outcome measures: 24-item list of somatic complaints (von Zerssen list), six-item headache impact test (HIT-6), tinnitus.

Results: For participants in the top decile of environmental far-field RF-EMF exposure in the baseline survey, in comparison to participants exposed below the median value, the change in the von Zerssen- and HIT-6-scores between the baseline and follow-up survey was -0.12 (95%-CI: -1.79 to 1.56) and -0.37 (95%-CI: -1.80 to 1.07) units, respectively. Environmental far-field exposure was computed with a validated exposure assessment model for the most relevant RF-EMF exposure sources. The odds ratio for developing tinnitus at follow-up was 0.18 (95%-CI: 0.02 to 1.51) for participants in the top decile of exposure in the baseline survey compared to participants below the median. Similarly, there was no association between non-specific symptoms or tinnitus and the use of mobile phones, information for which was derived from mobile phone call records from mobile phone companies. Furthermore, there was no indication that an increase in environmental far-field RF-EMF exposure or mobile phone use between baseline and follow-up was related to the development of non-specific symptoms or tinnitus.

Conclusions: This first cohort study on the association between RF-EMF exposure and health-related quality of life, using objective and well-validated exposure measures, does not suggest a detrimental effect of RF-EMF exposure on the development of non-specific symptoms after 1 year of exposure.

Introduction

Radio frequency electromagnetic field (RF-EMF) emitting sources like mobile phone base stations and handsets, broadcast transmitters or wireless LAN (W-LAN) are ubiquitous and exposure has been increasing over the past 20 years (Neubauer et al., 2007). This development has raised public concerns regarding potentially detrimental health effects of this technology, especially regarding effects on non-specific symptoms like headache (Röösli et al., 2004; Schreier et al., 2006; Schröttner and Leitgeb, 2008; Blettner et al., 2009).

Several studies have addressed potential health effects so far. Most studies were performed in laboratories, e.g (Regel et al., 2006; Cinel et al., 2008; Hillert et al., 2008). The advantage of laboratory trials is that the well-defined exposure setting allows for the exact determination of a person's exposure level as well as randomization and double-blinding. The disadvantages are that usually only a small study population can be investigated and that effects after prolonged exposure durations cannot be studied due to ethical and practical reasons. Such effects can only be addressed in epidemiological studies. However, sound assessment of RF-EMF exposure in everyday life is highly challenging (ICNIRP, 2009b). The use of crude exposure proxies, like the lateral distance to the closest mobile phone base station, has been shown to be inappropriate (Schüz and Mann, 2000; Bornkessel et al., 2007; Neubauer et al., 2007; Frei et al., 2010). More sophisticated exposure assessment methods such as spot or personal measurements need considerable efforts and thus, most epidemiological studies conducted so far were of cross-sectional design (Chia et al., 2000; Balikci et al., 2005; Thomas et al., 2008a; Berg-Beckhoff et al., 2009; Blettner et al., 2009; Mohler et al., 2010). The limitation of collecting exposure and health data at the same point in time is that it is difficult to draw conclusions about a causal relationship between exposure and health (Seitz et al., 2005). In addition, spurious exposure-outcome associations can be introduced if information bias or a nocebo effect, i.e. the development of symptoms due to concerns, is involved. Several laboratory trials have provided evidence for a nocebo effect (Röösli, 2008). In cross-sectional studies even inverse associations between exposure and health may be observed, if persons claiming to be electrohypersensitive (EHS), i.e. to develop symptoms due to RF-EMF exposure, avoid RF-EMF exposure, since such persons usually suffer more often from non-specific symptoms than the general population (Seitz et al., 2005; Landgrebe et al., 2009).

Due to the unknown biological mechanism of RF-EMFs below the thermal threshold, if there is any at all, it is unclear what aspect of the exposure is relevant for the development of non-specific symptoms. It might be conceivable that exposure at the head, usually mainly caused by sources operated close to the body (e.g. mobile and cordless phones), is most relevant for headache. On the other hand, exposure from environmental far-field sources like mobile phone base stations, which generally cause lower but whole-body exposures over longer time periods and also during nights, might play a role for non-specific symptoms of ill health.

In the framework of the QUALIFEX study (health related quality of life and radio frequency electromagnetic field exposure: prospective cohort study), we performed a baseline questionnaire survey in 2008 in a random population sample. One year later, a follow-up was conducted. The aim of this study was to investigate whether RF-EMF exposure at baseline or a change of RF-EMF exposure between baseline and follow-up was associated with the development of non-specific symptoms of ill health or tinnitus.

Methods

Study population

The recruitment strategy of the baseline survey is described in detail in Mohler et al. (2010). In brief, in May 2008 we sent out questionnaires entitled “environment and health” to 4000 randomly selected residents from the region of Basel, Switzerland, aged between 30 and 60 years. After one year, a follow-up was conducted by sending the same questionnaire to the respondents of the baseline survey. Non-responder interviews were conducted after both surveys by phone.

Written questionnaire

The written questionnaire was divided into three parts: the first part consisted of questions regarding the general health status and non-specific symptoms of ill health. The study participants were asked to fill in several standardized questions, namely the 24-item list of somatic complaints (von Zerssen) (von Zerssen, 1976) and the six-item headache impact test (HIT-6) (Kosinski et al., 2003). The von Zerssen-score ranges from 0 (no complaints) to 72 (severe complaints), and the HIT-6-score from 36 (no impact) to 78 (severe impact). In addition, the participants were asked whether they currently suffered from tinnitus. In the second part of the questionnaire, we assessed exposure to RF-EMF. Questions on exposure relevant characteristics and behaviors (see next paragraph) like the ownership of a mobile or cordless phone were included. The last part of the questionnaire contained questions on socio-demographic factors (e.g. age, gender). We also asked the participants whether they were electrohypersensitive (EHS) (defined as answering "yes" to either the question "Are you electrohypersensitive?" or to the question "Do you think that you develop detrimental health symptoms due to electromagnetic pollution in everyday life?").

Exposure assessment

We assessed exposure to environmental far-field sources as well as to sources operating close to the body. Regarding exposure to environmental far-field sources, we used two surrogates: firstly, we calculated mean RF-EMF from fixed site transmitters (mobile phone base stations and broadcast transmitters) at the residency of each study participant by means of a geospatial propagation model which had been developed and validated for the study region (Bürgi et al., 2008; Bürgi et al., 2010). Secondly, we used a predictive exposure assessment model to predict total personal RF-EMF far-field exposure. This model was developed and validated in an independent study sample of 166 residents from the same study region and is explained in detail in Frei et al. (2009a). Shortly, we collected exposure measurements during one week with the personal exposure meter EME Spy 120 and questionnaire data from these 166 volunteers. We identified the following relevant exposure predictors using multiple regression models: the modeled RF-EMF at the participants' home from the geospatial propagation model, modified by the type of house wall and type of window frames. Additionally, the ownership of wireless communication devices (W-LAN, mobile and cordless phones) and behavioral characteristics (amount of time spent in public transport vehicles or cars, percent full-time equivalent) were included into the model. The predictive exposure assessment model takes into account exposure from the following sources: broadcast transmitters, mobile phone handsets and base stations, DECT phones and wireless LAN. Exposure to mobile phone handsets and cordless phones represent phone calls of other persons, handovers of the personal or other mobile phones and the radiation of a cordless phone base station. The personal phone use was not considered in the model.

Local exposure at the head from sources operating in close proximity of the body was assessed by self-reported use of mobile and cordless phones. In addition, we asked participants for informed consent to obtain operator data of their private mobile phone use of the previous 6 months of each investigation.

In order to evaluate the occurrence of information bias or a nocebo effect, we asked participants to compare their exposure situation with the average Swiss population. An association between perceived exposure and health, independently of actual exposure, would be indicative of nocebo effects or information bias.

Statistical analyses

For the linear outcome variables (von Zerssen- and HIT-6-score), linear regression models were calculated and for the binary tinnitus variable logistic regression models. Four analyses were performed: Firstly, we conducted cross-sectional analyses for the baseline and follow-up survey. Secondly, we performed a cohort analysis and a change analysis. For the cohort analysis, we assessed the association between the exposure level at baseline and the change in health status between baseline and follow-up. Three exposure categories were defined: exposure below median (reference), exposure equal or above median up to the 90^{th} percentile, and the top exposure decile. In the change analysis, we examined whether the change in exposure between baseline and follow-up resulted in a change in health outcome. We compared the study participants with the 20% largest decrease and increase with the remaining 60% who experienced a smaller or no change of exposure between baseline and follow-up (reference).

All models were adjusted for age, sex, body mass index, stress, physical activity, smoking habits, alcohol consumption, education, marital status, degree of urbanity, nightshift work, believe in health effects due to RF-EMF exposure, use of sleeping drugs and general attitude towards the environment. In the cohort and change analyses, we considered the confounders at baseline and additionally adjusted the models for moving house between the two surveys. Missing values in the confounder variables at baseline were replaced with the information of the follow-up and vice versa. If values were missing for both, baseline and follow-up, they were replaced with values of either the most common category (categorical variables) or with the mean value (linear variables). In all models for environmental far-field exposure sources, we included (self-reported) use of mobile and cordless phones as co-exposures. Similarly, total personal far-field exposure (predictive exposure assessment model) was used as co-exposure variable in all models for mobile and cordless phone use, and all three exposure variables (environmental RF-EMF, cordless and mobile phone use) were included in the model for self-estimated exposure.

All models were tested for interaction between EHS status and the exposure measures in order to evaluate whether EHS individuals are differently affected by RF-EMF exposure. The interaction term was tested with likelihood-ratio tests, and the presented coefficients and odds ratios (ORs) represent the exposure-outcome association for the non-EHS individuals. All calculations were performed with the values for the power flux density (mW/m^2). Statistical analyses were carried out using STATA version 10.1 (StataCorp, College Station, TX, USA).

Results

Study participants

Response rate was 37% at baseline and 82% at follow-up (Figure 6-3). Reasons for non-eligibility were severe disabilities, death, incorrect addresses, absence during study time or language problems. Two respondents of the follow-up had to be excluded from the analyses because they went abroad after the baseline survey.

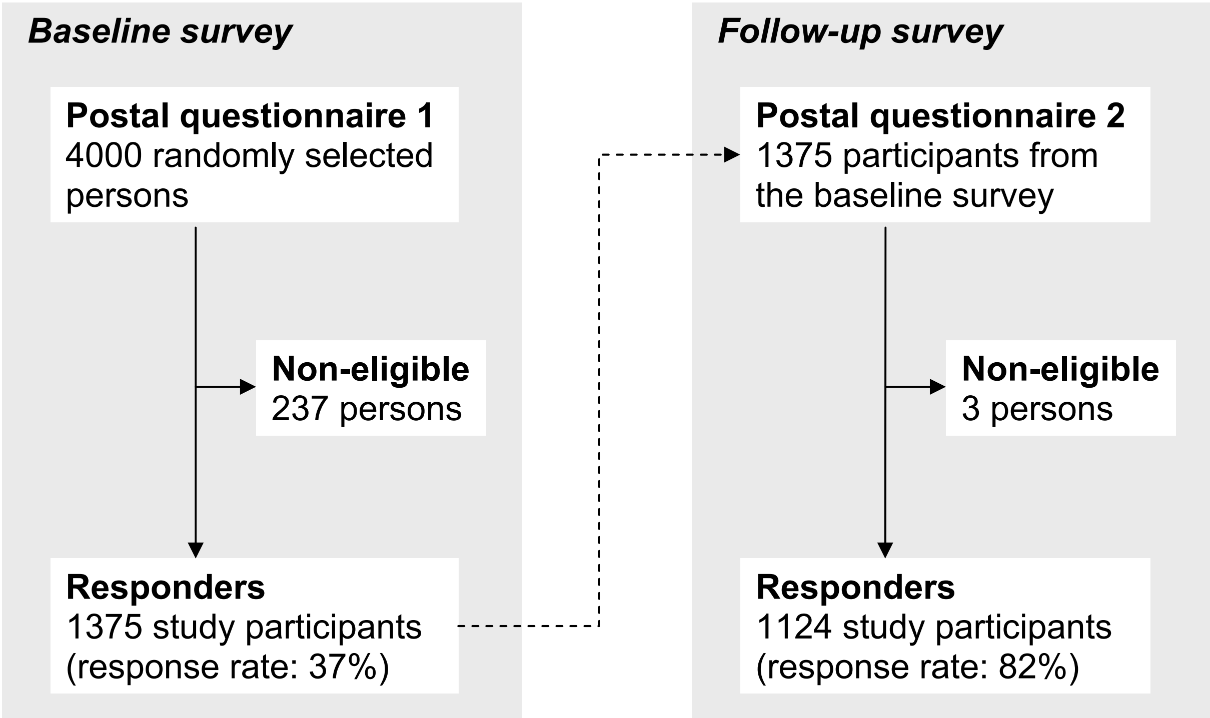

Figure 6-3: Schematic illustration of the study design and the response rates of the baseline and follow-up surveys.

The characteristics of the study participants of the baseline and follow-up survey included in the analyses are listed in Table 6-4. There are only small differences between the study participants who participated in the follow-up survey compared with those who only participated in the baseline survey. The mean age was 46 years (standard deviation (sd): 9 years) at baseline and 47 years (sd: 9 years) one year later at follow-up. Around 60% of the participants were females at baseline and follow-up.

RF-EMF exposure

Table 6-5 shows medians, 90^{th} percentiles and maxima of the different exposure surrogates at baseline and follow-up. With respect to total personal far-field exposure (derived from the predictive exposure assessment model) and residential exposure to fixed site transmitters (derived from the predictive exposure assessment model), the exposure distributions were very similar at baseline and follow-up. Mean total personal far-field exposure was 0.12 mW/m^2 (0.21 V/m) at baseline and 0.13 mW/m^2 (0.22 V/m) at follow-up. Mean modeled residential exposure to fixed site

Table 6-4: Characteristics of study participants at baseline and follow-up

	Baseline survey (n=1375)	%	Follow-up survey (n=1122)[a]	%
Age (years)				
<41	407	*29.6*	297	*26.5*
41-50	490	*35.6*	357	*31.8*
>51	478	*34.8*	468	*41.7*
Sex				
Female	798	*58.0*	678	*60.4*
Male	577	*42.0*	444	*39.6*
Health status				
(Very) good	1223	*89.7*	983	*88.6*
Half-half	122	*8.9*	112	*10.1*
(Very) bad	19	*1.4*	14	*1.3*
Educational level				
None	89	*6.6*	57	*5.2*
Apprenticeship	663	*48.5*	523	*47.8*
Higher education	615	*45.0*	515	*47.0*
Believe in health effects due to RF-EMF exposure[b]				
No	82	*6.0*	53	*4.7*
Yes	1069	*77.7*	874	*77.9*
Don't know/missing	224	*16.3*	195	*17.4*
Electromagnetic hypersensitivity				
No	825	*60.0*	642	*57.2*
Yes	294	*21.4*	247	*22.0*
Don't know/missing	256	*18.6*	233	*20.8*
Self-reported RF-EMF exposure[c]				
Lower	403	*29.3*	397	*35.4*
Equal	576	*41.9*	492	*43.9*
Higher	105	*7.6*	69	*6.1*
Don't know/missing	291	*21.2*	164	*14.6*

[a] Two responders of the follow-up were excluded from the analyses because they went abroad after the baseline survey.
[b] Question: “Do you think that there are persons who develop adverse health effects due to electromagnetic pollution”
[c] In comparison with the average Swiss population

Table 6-5: Exposure levels to different exposure sources in the study participants at baseline and follow-up and change between baseline and follow-up.

	Baseline (n=1375)	Follow-up (n=1122)	Change (n=1122)		
			Decrease	No change	Increase
Total personal far-field exposure (mW/m²)[a]					
Median	0.12	0.12	-0.04	0.00	0.05
90th percentile	0.17	0.18	-0.07	0.03	0.09
Maximum	0.47	0.40	-0.21	0.03	0.18
Residential exposure to fixed site transmitters (mW/m²)					
Median	0.01	0.01	0.00	0.00	0.00
90th percentile	0.05	0.05	-0.02	0.00	0.03
Maximum	1.43	1.43	-0.21	0.00	0.62
Mobile phone use (self-reported) (h/week)					
Median	0.23	0.22	-0.94	0.00	1.05
90th percentile	3.50	3.50	-4.23	0.08	6.42
Maximum	29.75	21.00	-21.06	0.15	17.50
Mobile phone use (operator data) (h/week)[b]					
Median	0.16	0.16	-0.50	-0.01	0.15
90th percentile	1.33	0.76	-1.61	0.02	0.50
Maximum	8.61	6.27	-3.18	0.04	5.38
Cordless phone use (self-reported) (h/week)[c]					
Median	0.35	0.35	-0.88	0.00	1.75
90th percentile	4.67	4.67	-4.61	0.35	4.67
Maximum	9.33	9.33	-9.28	0.58	9.33

[a] Mean exposure to relevant far-field exposure sources excluding personal use of mobile and cordless phones
[b] n=539/424 at baseline/follow-up
[c] similar values due to the use of categories in the questionnaire

transmitters (geospatial propagation model) was 0.02 mW/m² (0.09 V/m) at baseline and follow-up. The study participants reported to use their mobile phones at baseline (follow-up) on average during 1.18 hours (1.13 hours) and their cordless phones during 1.26 hours (1.28 hours) per week. Persons for whom operator data were available used their mobile phone on average during 31 minutes per week at baseline (n=539) and during 21 minutes per week at follow-up (n=424). The self-reported use of the private mobile phone restricted to the persons providing operator data was 28 minutes at baseline and 30 minutes at follow-up.

Somatic complaints: the von Zerssen-score

At baseline, the average von Zerssen-score was 12, ranging from 0 to 57. At follow up, it was 13, ranging from 0 to 66. Web table 6-4 shows the adjusted coefficients and their 95% confidence intervals (CIs) of the linear regression models for the cross-sectional surveys (2008 and 2009). Except for slight tendencies of an inverse association between self-reported mobile and cordless phone use and somatic complaints, no consistent exposure-outcome association could be observed. The same holds for the corresponding data for the cohort analysis (Table 6-6). However, this is not confirmed in the operator data. In the change analysis, a very slight tendency could be seen in the self-reported and operator data that both, persons decreasing and increasing their mobile phone use, suffer less from somatic complaints. In the cohort analysis, a trend for suffering more from somatic complaints for individuals who believed to be more exposed to RF-EMF in comparison to the Swiss average was found. This was also observed in the cross-sectional analyses.

Headache: the HIT-6 score

The average HIT-6-score was 46 at baseline (range: 36-78) and at follow-up (range: 36-74). In the cross-sectional analyses (Web table 6-5), we found rather inverse associations for most analyses, except for self-estimated exposure. In the cohort analysis (Table 6-7), the headache score tended to increase between baseline and follow-up for the heaviest mobile phone users according to the operator data at baseline. In the change analysis, both, in- and decrease of mobile phone use was accompanied with a decrease of the HIT-6-score. We found that the HIT-6-score increased most for individuals who believed to be more exposed to RF-EMF compared to the Swiss average at baseline (cohort analysis) or for individuals who rated their own exposure status higher at follow-up than at baseline (change analysis).

Tinnitus

128 (9%) persons reported to suffer from tinnitus at baseline and 131 (12%) at follow-up. Twenty persons reported to suffer from tinnitus only at baseline and 44 only at follow-up. No consistent exposure-outcome association was observed in the cross-sectional (Web table 6-6) analyses. In the cohort and change analysis (Table 6-8), a slightly higher risk of developing tinnitus was associated with the mobile phone operator data. Most of the other associations suggest a tendency for an inverse association between RF-EMF exposure and tinnitus.

Comparison of the effect in EHS and non-EHS individuals

There was no consistent difference between EHS and non-EHS individuals regarding the exposure-outcome association. For the 72 tested models the likelihood-ratio test suggests a difference between the two groups in eleven (15.3%) of the models. In two of the cases, a more pronounced positive exposure-outcome association was found for the EHS group compared to the non-EHS group and in eight of the cases a more pronounced positive exposure-outcome association was found for the non-EHS group. In one case, we found a mixed pattern in the three exposure categories.

Table 6-6: Results of the cohort analysis and change analysis showing the association between the different exposure surrogates and the von Zerssen-score (regression coefficients and 95% confidence intervals (CI) of the three exposure categories adjusted for relevant confounders[a]). Negative coefficients indicate an inverse association and positive coefficients a positive association between exposure and somatic complaints.

	COHORT ANALYSIS (n=1058)			CHANGE ANALYSIS (n=1042)		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	Decrease (95%-CI)	No change	Increase (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	0	0.64 (-0.37;1.66)	-0.12 (-1.79;1.56)	0.25 (-0.95;1.46)	0	0.12 (-1.08;1.31)
Exposure to fixed site transmitters	0	0.18 (-0.79;1.15)	-0.24 (-1.89;1.41)	0.01 (-1.16;1.18)	0	0.82 (-0.42;2.06)
Close to body exposure						
Mobile phone use (self-reported)	0	-0.44 (-1.55;0.66)	***-1.79 (-3.56;-0.02)***	***-1.19 (-2.38;-0.00)***	0	***-1.43 (-2.67;-0.18)***
Mobile phone use (operator data)[b)]	0	-0.99 (-2.46;0.47)	0.12 (-2.58;2.83)	-1.13 (-3.25;1.00)	0	-0.60 (-2.67;1.46)
Cordless phone use (self-reported)	0	0.50 (-0.46;1.46)	0.01 (-3.01;3.04)	-0.26 (-1.41;0.89)	0	-0.17 (-1.52;1.18)
	equal	lower (95%-CI)	higher (95%-CI)	lower (95%-CI)	equal	higher (95%-CI)
Self-estimated exposure	0	-0.04 (-1.03;0.95)	***2.25 (0.03;4.46)***	-0.17 (-1.46;1.13)	0	-0.02 (-1.26;1.22)

[a]adjusted for age, sex, body mass index, stress, physical activity, smoking habits, alcohol consumption, education, marital status, degree of urbanity, nightshift work, believe in health effects due to RF-EMF exposure, use of sleeping drugs, general attitude towards the environment and for moving house between the two surveys.

[b]data from 441 (cohort analysis) and 280 (change analysis) persons

Table 6-7: Results of the cohort analysis and change analysis showing the association between the different exposure surrogates and the HIT-6-score (regression coefficients and 95% confidence intervals (CI) of the three exposure categories adjusted for relevant confounders[a]). Negative coefficients indicate an inverse association and positive coefficients a positive association between exposure and headache.

	COHORT ANALYSIS (n=1080)			CHANGE ANALYSIS (n=1063)		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	Decrease (95%-CI)	No change	Increase (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	0	0.00 (-0.89;0.88)	-0.37 (-1.80;1.07)	0.23 (-0.83;1.30)	0	-0.24 (-1.28;0.80)
Exposure to fixed site transmitters	0	0.91 (0.07;1.75)	1.01 (-0.40;2.43)	0.52 (-0.50;1.54)	0	0.06 (-1.03;1.15)
Close to body exposure						
Mobile phone use (self-reported)	0	-0.78 (-1.75;0.19)	-0.49 (-2.02;1.03)	-0.30 (-1.33;0.74)	0	-0.33 (-1.42;0.76)
Mobile phone use (operator data)[b)]	0	0.16 (-1.16;1.48)	2.17 (-0.25;4.60)	-0.95 (-3.06;1.16)	0	-1.64 (-3.67;0.39)
Cordless phone use (self-reported)	0	-0.23 (-1.06;0.60)	-0.03 (-2.68;2.62)	-0.26 (-1.27;0.75)	0	0.24 (-0.93;1.41)
	equal	lower (95%-CI)	higher (95%-CI)	lower (95%-CI)	equal	higher (95%-CI)
Self-estimated exposure	0	0.05 (-0.82;0.91)	1.35 (-0.58;3.28)	0.37 (-0.77;1.50)	0	***1.18 (0.11;2.25)***

[a]confounders see Table 6-6
[b]data from 451 (cohort analysis) and 284 (change analysis) persons

Table 6-8: Results of the cohort analysis and change analysis showing the association between the different exposure surrogates and tinnitus (odds ratios (OR) and 95% confidence intervals (CI) of the three exposure categories) adjusted for relevant confounders[a]). ORs<1 indicate an inverse and >1 a positive association between exposure and tinnitus.

	COHORT ANALYSIS (n=1112)			CHANGE ANALYSIS (n=1092)		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	Decrease (95%-CI)	No change	Increase (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	1	1.04 (0.51;2.11)	0.18 (0.02;1.51)	1.17 (0.37;3.72)	1	1.34 (0.52;3.49)
Exposure to fixed site transmitters	1	0.94 (0.39;2.25)	1.39 (0.36;5.41)	1.77 (0.68;4.61)	1	1.67 (0.58;4.80)
Close to body exposure						
Mobile phone use (self-reported)	1	0.62 (0.27;1.42)	0.83 (0.21;3.22)	0.93 (0.34;2.53)	1	0.61 (0.19;1.95)
Mobile phone use (operator data)[b)]	1	2.14 (0.42;11.02)	2.36 (0.16;34.86)	0.07 (0.00;2.95)	1	1.70 (0.25;11.59)
Cordless phone use (self-reported)	1	0.46 (0.19;1.10)	0.00 -	0.95 (0.35;2.57)	1	0.90 (0.28;2.94)
	equal	lower (95%-CI)	higher (95%-CI)	lower (95%-CI)	equal	higher (95%-CI)
Self-estimated exposure	1	0.54 (0.19;1.50)	0.95 (0.11;8.24)	1.35 (0.47;3.90)	1	0.58 (0.16;2.14)

[a]confounders see Table 6-6
[b]data from 455 (cohort analysis) and 286 (change analysis) persons

Discussion

Our findings do not suggest an association between RF-EMF exposure in everyday life and the development of self-reported non-specific symptoms and tinnitus. Neither exposure to environmental far-field sources nor to sources operating in close proximity of the body showed an effect. No consistent evidence for a difference in the exposure-outcome relationship between EHS and non-EHS individuals could be observed. We found an indication for a nocebo effect and/or information bias in relation with the development of non-specific symptoms.

Strengths and limitations

So far, in no other study a cohort design was applied to study potential RF-EMF exposure effects on non-specific symptoms, which allows for more robust conclusions. Although self-reported, the subjective symptoms that we assessed (von Zerssen and HIT-6) were based on standardized questions. To our knowledge, our study used the most comprehensive exposure assessment method by considering potential effects of both exposure to environmental far-field sources and sources operating close to the body. For both types of exposure, we used objective exposure data. The elaborate predictive exposure assessment model includes all relevant RF-EMF exposure sources in everyday life in the frequency range of 88-2500 MHz. It is based on the geospatial propagation model that includes very accurate parameters from all fixed site transmitters of the study region, complemented with data on relevant behaviors. The feasibility and reproducibility of the prediction model as well as of the geospatial propagation model was previously demonstrated (Frei et al., 2009a; Bürgi et al., 2010). From 39.2% of the study participants at baseline and of 37.8% at follow-up, we collected objective traffic records of all ingoing and outgoing calls of the previous 6 months of each investigation from the mobile phone operators, which has to our knowledge not been done in previous studies investigating the effect of mobile phone use on the development of non-specific symptoms. Unfortunately, we were only able to obtain traffic records of private, but not business-related phone calls. About 25% of the individuals who agreed to provide their traffic records at baseline and follow-up owned a business mobile phone as well. This may have led to some exposure misclassification.

Another limitation was the rather low participation rate of 37% in the baseline survey. If persons attributing health effects to RF-EMF exposure were more motivated to participate in our study, selection bias is of concern for the cross-sectional analyses. We found a similar HIT-6-score and even slightly lower von Zerssen-score in comparison to a recent German study, where persons were selected from a nationwide survey and the participation rate was very high (85%) (Berg-Beckhoff et al., 2009). Therefore there is no evidence that persons suffering from more symptoms were more likely to participate. As we had a very high participation rate of 82% in the follow-up, selection bias is less of a problem for the cohort and the change analyses.

Interpretation

In general, we found no evidence that exposure to RF-EMF in everyday life is associated with the development of non-specific symptoms or tinnitus. We observed only very few statistically significant effects, which were not consistent. Given the numerous tests we performed, a few statistically significant effects can be expected by chance. We conducted a large number of analyses because in the absence of a known biological mechanism in the low dose range, it was unclear which aspect of exposure might be relevant for health disturbances, if any at all. We did not apply a formal multiple endpoint correction (e.g. Bonferroni correction). Instead we checked the consistency and biological plausibility of similar analyses. The statistical power of the study was adequate to detect relatively small changes of the health outcome: a post-hoc power analysis revealed that a change of 1.6 points in the von Zerssen-score and of 1.4 point in the HIT-6-score could be detected with a power of 80%. To compare, the von Zerssen and HIT-6-score of persons who felt disturbed by noise of their neighbors were higher by 5.1 and 2.8 points, respectively, in comparison to persons who did not feel disturbed.

With regard to environmental far-field sources, our findings are in line with laboratory trials investigating acute effects of whole-body mobile phone base station exposure (Röösli et al., in press). In epidemiological studies on environmental far-field sources, there is a tendency that effects were found in studies where crude or subjective exposure surrogates were used (e.g. the lateral distance to the closest mobile phone base station (Navarro et al., 2003; Santini et al., 2003)), while for studies using objective exposure surrogates no effect were found (Heinrich et al., 2007; Thomas et al., 2008a; Berg-Beckhoff et al., 2009; Blettner et al., 2009; Kühnlein et al., 2009). Regarding close to body sources, no acute effects of mobile phones like exposure were observed in laboratory trials (Röösli, 2008; Stovner et al., 2008; Nam et al., 2009) except for one study, where a higher headache score was found after applying a 3h mobile phone-like exposure (Hillert et al., 2008). Our self-reported data on mobile phone use show rather an inverse association with non-specific symptoms and our results contradict earlier cross-sectional epidemiological studies, where positive associations were found for non-specific symptoms (Chia et al., 2000; Balikci et al., 2005). One reason for this discrepancy might be that the participants in our study were more accurate in reporting their mobile phone use because they were aware that we collected the data from their mobile phone operators as well. Thus, information bias may have been prevented. Another factor which might have played an important role in previous epidemiological studies where effects were found is selection bias and nocebo. Selection bias, information bias and nocebo, are of less concern in our cohort and change analyses.

In the mobile phone operator data, the cohort analysis suggests a slightly increased headache score for persons in the top exposure decile at baseline. This, however, is not confirmed in the change analysis. With regard to tinnitus, we found a tendency in the cohort analysis that individuals above the 50^{th} percentile of mobile phone use (operator data) at baseline had a higher risk of suffering from tinnitus at follow-up. This tendency could also be observed in the change analysis. However, these results are based on only 25 and 14 tinnitus cases, respectively. Previous research does not suggest an effect of RF-EMF exposure on the development of tinnitus (Davidson and Lutman, 2007; Mortazavi et al., 2007; Thomas et al., 2008a).

Generally, the mean exposure levels to environmental far-field RF-EMF sources in our study population were by several orders of magnitude below the current standard limits. Also, we observed only small exposure differences between baseline and follow-up. We can therefore only state that effects due to the small exposures and exposure changes that are experienced nowadays are unlikely. However, we cannot draw conclusions about health effects which might occur due to exposure changes in the future or at levels close to the standard limits.

Due to the fact that EHS individuals might have a complex behavior regarding EMF exposure, we included an interaction term for EHS individuals which allowed for different exposure effects for EHS and non-EHS individuals. We expected that RF-EMF avoidance behavior and nocebo would be present in particular in EHS individuals. However, no consistent differences between EHS and non-EHS individuals in the exposure-outcome association and therefore no indication that EMF exposure is more harmful for EHS individuals was found. Information bias is expected to be present for EHS and non-EHS individuals. We found a tendency for EHS as well as non-EHS individuals who estimated themselves to be less exposed to RF-EMF compared to the general Swiss population to suffer less from non-specific symptoms and for those who estimated their own exposure to be higher to suffer more from non-specific symptoms. A more detailed analysis of the characteristics and exposure effects in the EHS collective of this survey is given in Röösli et al. (submitted).

To conclude, we did not find evidence for a detrimental effect of exposure to RF-EMF in everyday life on the development of non-specific symptoms or tinnitus. These results, however, are only valid for relatively small levels of RF-EMF exposure that occur today. We cannot make firm conclusions about higher exposure levels or more dramatic changes of exposure that might be induced by the future technical development.

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What is already known on this topic:

Exposure to radio frequency electromagnetic fields (RF-EMF), as produced by mobile phones, has been linked to non-specific symptoms such as headaches in some previous epidemiological studies

Drawbacks of previous studies include a cross-sectional design and the use of self-reported exposure, thus possibly introducing selection and information biases

What this study adds:

The results of this study do not suggest a detrimental effect of RF-EMF on the development of non-specific symptoms after 1 year of exposure

This study allows for more robust conclusions on the association between RF-EMF exposure and health-related quality of life due to its longitudinal design and the use of objective exposure data, thus minimizing selection and information bias

Web table 6-4: Results of the two cross-sectional analyses (baseline and follow-up) showing the association between the different exposure surrogates and the von Zerssen-score (regression coefficients and 95% confidence intervals (CI) of the three exposure categories adjusted for relevant confounders[a]). Negative coefficients indicate an inverse association and positive coefficients a positive association between exposure and somatic complaints.

	BASELINE SURVEY 2008 (n=1310)			**FOLLOW-UP SURVEY 2009 (n=1065)**		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	0	-0.77 (-1.81;0.28)	-0.60 (-2.34;1.14)	0	1.14 (-0.10;2.37)	0.45 (-1.60;2.49)
Exposure to fixed site transmitters	0	-0.39 (-1.40;0.62)	1.20 (-0.45;2.85)	0	0.07 (-1.10;1.24)	0.67 (-1.35;2.69)
Close to body exposure						
Mobile phone use (self-reported)	0	-0.78 (-1.92;0.35)	-1.20 (-2.94;0.54)	0	***-1.66*** ***(-2.96;-0.35)***	-1.28 (-3.57;1.00)
Mobile phone use (operator data)[b)]	0	0.28 (-1.32;1.87)	0.11 (-2.71;2.94)	0	-0.15 (-2.00;1.70)	-0.09 (-3.31;3.14)
Cordless phone use (self-reported)	0	-0.38 (-1.39;0.63)	-1.31 (-4.20;1.58)	0	0.00 (-1.15;1.15)	-0.80 (-3.91;2.31)
	equal	lower (95%-CI)	higher (95%-CI)	equal	lower (95%-CI)	higher (95%-CI)
Self-estimated exposure	0	-0.25 (-1.28;0.78)	0.36 (-1.78;2.51)	0	-0.49 (-1.74;0.75)	1.20 (-1.99;4.38)

[a]adjusted for age, sex, body mass index, stress, physical activity, smoking habits, alcohol consumption, education, marital status, degree of urbanity, nightshift work, believe in health effects due to RF-EMF exposure, use of sleeping drugs and general attitude towards the environment.
[b]data from 523 (baseline) and 409 (follow-up) persons

Web table 6-5: Results of the two cross-sectional analyses (baseline and follow-up) showing the association between the different exposure surrogates and the HIT-6-score (regression coefficients and 95% confidence intervals (CI) of the three exposure categories adjusted for relevant confounders[a]). Negative coefficients indicate an inverse association and positive coefficients a positive association between exposure and headache.

	BASELINE SURVEY 2008 (n=1341)			**FOLLOW-UP SURVEY 2009 (n=1085)**		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	0	0.15 (-0.88;1.18)	-0.10 (-1.81;1.60)	0	0.54 (-0.66;1.73)	-0.05 (-2.01;1.91)
Exposure to fixed site transmitters	0	***-1.23*** ***(-2.22;-0.24)***	-0.76 (-2.37;0.86)	0	-0.50 (-1.63;0.64)	-0.54 (-2.50;1.42)
Close to body exposure						
Mobile phone use (self-reported)	0	0.34 (-0.77;1.46)	-0.52 (-2.23;1.19)	0	0.03 (-1.23;1.28)	-0.18 (-2.32;1.97)
Mobile phone use (operator data)[b)]	0	-0.74 (-2.38;0.91)	-2.33 (-5.24;0.59)	0	-0.14 (-2.06;1.79)	-0.68 (-4.07;2.71)
Cordless phone use (self-reported)	0	0.96 (-0.03;1.95)	-0.84 (-3.71;2.03)	0	1.06 (-0.04;2.17)	0.68 (-2.32;3.68)
	equal	lower (95%-CI)	higher (95%-CI)	equal	lower (95%-CI)	higher (95%-CI)
Self-estimated exposure	0	-0.46 (-1.47;0.55)	0.02 (-2.07;2.10)	0	-0.47 (-1.66;0.73)	2.44 (-0.49;5.38)

[a]confounders see Web table 6-4
[b]data from 528 (baseline) and 416 (follow-up) persons

Web table 6-6: Results of the two cross-sectional analyses (baseline and follow-up) showing the association between the different exposure surrogates and tinnitus (odds ratios (OR) and 95% confidence intervals (CI) of the three exposure categories adjusted for relevant confounders[a]). ORs<1 indicate an inverse and >1 a positive association between exposure and tinnitus.

	BASELINE SURVEY 2008 (n=1359)			**FOLLOW-UP SURVEY 2009 (n=1100)**		
	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)	<50th perc.	50th-90th percentile (95%-CI)	>90th percentile (95%-CI)
Far-field environmental exposure						
Total personal far-field exposure	1	0.72 (0.44;1.19)	0.92 (0.44;1.93)	1	1.11 (0.68;1.82)	0.65 (0.25;1.64)
Exposure to fixed site transmitters	1	0.78 (0.49;1.25)	0.59 (0.25;1.39)	1	1.18 (0.74;1.89)	0.63 (0.24;1.69)
Close to body exposure						
Mobile phone use (self-reported)	1	0.80 (0.48;1.36)	0.69 (0.30;1.59)	1	0.80 (0.46;1.38)	1.19 (0.50;2.83)
Mobile phone use (operator data)[b)]	1	0.60 (0.28;1.30)	0.42 (0.08;2.14)	1	0.72 (0.32;1.63)	0.87 (0.21;3.62)
Cordless phone use (self-reported)	1	1.26 (0.79;2.01)	1.00 (0.21;4.71)	1	0.71 (0.44;1.14)	0.63 (0.14;2.88)
	equal	lower (95%-CI)	higher (95%-CI)	equal	lower (95%-CI)	higher (95%-CI)
Self-estimated exposure	1	1.21 (0.76;1.93)	1.25 (0.52;3.01)	1	0.85 (0.51;1.41)	0.83 (0.23;2.93)

[a]confounders see Web table 6-4
[b]data from 533 (baseline), 420 (follow-up) persons

7 Summary of the main findings

In the following, the results of the aims outlined in chapter 2.2 are presented as short summaries of the main findings that were discussed in detail in the respective articles.

Aim 1: *To address, evaluate and solve methodological and practical challenges arising from the use of the personal exposimeter EME Spy 120.*

Nondetects: On average, between 82.7% (GSM 1800 downlink) and 99.8% (UMTS uplink) of the measurements were below the detection limit in our data. We found that the robust regression on order statistics (ROS) method produces more reliable summary statistics than the naïve approach used by the EME Spy 120 software, where all values below the detection limit of 0.05 V/m are set to 0.05 V/m. The naïve approach considerably overestimates exposure contributions from minor RF-EMF sources. Therefore, using the naïve approach would lead to an underestimation of the exposure range in the population.

Temporal stability: The mean exposure level of all study participants calculated with the temporal calibration factors of the exposimeters was 0.12 mW/m^2 (14.1% lower than the mean without calibration factors). Also, the contributions of the different RF-EMF sources to the total exposure remained very similar. Exposimeter measurements therefore remain relatively stable over time.

Measuring accuracy: The accuracy of exposimeter measurements depends on several factors. We found that the carrier frequency is of relevance: for example in the UMTS uplink band (1920-1980 MHz), the exposimeter underestimates the true field at 1980 MHz but overestimates it at 1920 MHz. For TDMA based services (GSM, DECT, Tetrapol), the accuracy also depends on the number of active time slots. For GSM downlink we saw that no signal is detected unless all 8 time slots are active. For the GSM uplink, DECT and Tetrapol we found that the less time slots were active, the higher the overestimation of the exposimeter reading. Except for radiation from the DECT base station, a linear behaviour can be observed for different power levels. The device is not perfectly isotropic, i.e. we found some deviations in the measured values when the exposimeter was oriented horizontally to the wave compared to when placed vertically to the wave. Multiple signals in the same frequency band are not reliably detected by the exposimeter. Out of band response was found for several frequency bands. Device-dependent variability was observed.

Use of sources close to the body: Our results show that personal mobile and cordless phone use contributes relatively little to the personal RF-EMF measurements. Nevertheless, mean values calculated from all measurements were statistically significantly elevated (0.15 mW/m^2) compared to mean values calculated when measurements during personal phone use were omitted (0.13 mW/m^2) ($p<0.001$). Exposimeter values containing personal phone use were shown to reliably discriminate between individuals' exposure levels to far-field environmental sources: the Spearman correlation between mean values calculated with and without personal phone use was 0.94 (95%-CI: 0.92–0.96).

Aim 2: *To characterise the distribution of personal RF-EMF exposure levels in a Swiss population sample.*

The mean exposure to all RF-EMF sources measured by the exposimeter over one week was 0.13 mW/m^2 (0.22 V/m). The individual means ranged from 0.014 to 0.881 mW/m^2 (0.07 to 0.58 V/m). The most important exposure sources were mobile phone base stations (32.0%), mobile phones (29.1%) and DECT cordless phones (22.7%). Radio and TV broadcast (5.9% and 5.8%, respectively), W-LAN (4.1%) and Tetrapol (0.3%) were minor exposure sources. The highest exposure levels were measured when travelling in trains (1.16 mW/m^2), tramways and buses (0.36 mW/m^2). Daytime measurements (0.16 mW/m^2) were on average higher than measurements during the night (0.08 mW/m^2). Mean exposure levels were well below the reference values. The mean exposure measured in the second week correlated well with the values of the first week for the participants who took part in the validation study (Spearman correlation coefficient: 0.61).

> *Aim 3*: *To develop a method for individual RF-EMF exposure assessment and to evaluate alternative exposure assessment methods*

Geospatial propagation model: The prediction of RF-EMF from fixed site transmitters showed a good accuracy when comparing the mean modelled values with the values obtained from spot measurements. The Spearman correlation coefficients (kappa values) of the model predictions were 0.64 (0.48) with outdoor street measurements, 0.66 (0.44) with indoor measurements (bedroom of participants from the exposimeter study), and 0.67 (0.53) with measurements in front of the bedroom windows of the study participants. This shows that the model performs well at outdoor locations but can also successfully predict exposure at indoor locations.

Full exposure prediction model: We could show that it is feasible to model individual exposure to the most relevant environmental far-field RF-EMF sources. We identified the following exposure relevant factors:

- the modelled RF-EMF at the participants' home derived from the geospatial propagation model
- the type of house wall (concrete vs. wood/brick)
- the type of window frame (metal vs. wood/plastic)
- owning a mobile phone
- owning W-LAN
- presence of a cordless phone in the bedroom
- presence of a cordless phone at the place where the study participant spends most of his/her time during daytime
- percent full-time equivalent spent at an external workplace
- amount of time spent in public transport
- amount of time spent in cars

The proportion of variance explained (R^2) by the prediction model was 0.52. The modelled exposure from the geospatial propagation model was shown to be an important predictor: using it as the only exposure predictor in the model revealed an R^2 of 0.25. The analysis of the agreement between calculated and measured RF-EMF showed a sensitivity of 0.56 and a specificity of 0.95 (cut-off: 90^{th} percentile).

The model also reliably predicted the data of the validation study, which were not used for the model development (sensitivity: 0.67, specificity: 0.96). This shows that the prediction model can be used to quantify mean exposure for a period of several months.

Evaluation of alternative exposure assessment methods: With regard to the ability of different exposure assessment methods to reliably distinguish between the individuals' exposure levels, we found that the full exposure prediction model correlated best with the personal exposimeter measurements (Spearman correlation coefficient (r_s)=0.50 (95%-CI: 0.37 to 0.61)). We observed moderate correlations of the personal measurements with the spot measurements in the bedrooms (r_s=0.42 (95%-CI: 0.27 to 0.55)) and with the values derived from the geospatial model for residential exposure from fixed site transmitters (r_s=0.28 (95%-CI: 0.14 to 0.42)). The use of the geo-coded distance to the closest fixed site transmitter showed a very low correlation with the personal measurements (r_s=-0.03 (95%-CI: -0.18 to 0.12)) and can therefore not be recommended for the usage in epidemiological studies. Similarly, self-estimated exposure was not correlated with actual exposure (r_s=0.06 (95%-CI: -0.10 to 0.21)).

Aim 4: *To study potential health effects resulting from RF-EMF exposure.*

Systematic review on health effects due to RF-EMF exposure: Our systematic review revealed that in most of the provocation studies performed in laboratories, no association between exposure to mobile phone base stations and the development of acute symptoms during or shortly after exposure was found. The sporadically observed associations did not show a consistent pattern in terms of symptoms or types of exposure (GSM 900, GSM 1800 or UMTS). Studies evaluating the ability to perceive RF-EMF did not find a tendency that participants (neither EHS nor non-EHS individuals) were able to detect RF exposure better than expected by chance. With regard to epidemiological studies, we observed that the more sophisticated the exposure assessment was carried out, the less likely an effect was reported. The present research does therefore not indicate adverse health effects resulting from exposure to mobile phone base stations at levels typically encountered in our everyday environment. However, no firm conclusions about health effects from long-term exposure in everyday life can be drawn due to lacking data.

Effects of RF-EMF exposure on non-specific symptoms and tinnitus: Our analyses do not suggest an association between RF-EMF exposure in everyday life and somatic complaints, headache, sleep impairment or tinnitus. In the baseline survey, the risk for excessive daytime sleepiness (ESS) was 0.58 (95%-CI: 0.31 to 1.05) for the participants in the top exposure decile (the ten percent highest exposed participants) according to our full exposure prediction model, and 1.11 (95%-CI: 0.50 to 2.44) for self-reported sleep disturbances (SQS). Regarding the other outcomes, neither the cross-sectional, nor the cohort or change analyses showed a consistent association between RF-EMF exposure and somatic complaints (von Zerssen), headache (HIT-6) or tinnitus. For persons in the top exposure decile of total environmental far-field RF-EMF exposure computed by the full exposure prediction model at baseline, the von Zerssen score changed by -0.12 (95%-CI: -1.79 to 1.56) and the HIT-6-score by -0.37 (95%-CI: -1.80 to 1.07) between baseline and follow-up (a score below 0 indicates less symptoms at follow-up). The risk of developing tinnitus between baseline and follow-up for the participants in the top exposure decile at baseline was 0.30 (95%-CI: 0.07 to 1.41). The change in the von Zerssen- and HIT-6-score for individuals who were more exposed at follow-up was 0.12 (95%-CI: -1.08 to 1.31) and -0.24 (95%-CI: -1.28 to 0.80), respectively. Moreover, we found no consistent association between duration of mobile and cordless phone use and any of the studied health outcomes.

8 General discussion

The specific findings of this thesis have been discussed in detail in the respective articles. In this chapter, more general aspects of the results are discussed. The results are placed in context to the previous literature and the implications for further research are presented. The discussion is structured following the four predefined aims specified in chapter 2.2.

8.1 Methodological challenges and evaluation of the EME Spy 120

Summary statistics with nondetects

Several personal measurement studies using exposimeters have been conducted so far, e.g. in Germany (Thomas et al., 2008a; Thomas et al., 2008b; Kühnlein et al., 2009; Thomas et al., 2010), France (Viel et al., 2009a; Viel et al., 2009b), Belgium (Joseph et al., 2008), Hungary (Thuróczy et al., 2008) and Slovenia (Valic et al., 2009). As in QUALIFEX, large proportions of nondetects were observed in these studies. We developed a method to deal with this problem by applying robust regression on order statistics (ROS). We are convinced that summary statistics are more reliable and more informative when calculated using robust ROS than when based on a naïve approach. Summary statistics calculated using robust ROS are more resistant to any non-normality errors and may thus be particularly appropriate for exposimeter data with a large proportion of censored data. However, statistics derived from ROS models of data with more than 80% censored values are tenuous (Helsel, 2005; Lee and Helsel, 2005). In frequency bands like Tetrapol or TV3, the percentage of nondetected values was on average over 99%. During analyses we sometimes observed that implausible values were computed by the robust ROS method, as currently implemented in the R statistical software. Since the distribution of the values below the detection limit depends on the values above the detection limit, a problem arises if the detected values are all of the same field strength: for example, if only three out of 7’000 measurements are above the detection limit and these three measurements are all exactly 0.08 V/m, the mean value calculated by ROS will be 0.08 V/m, which is not realistic. In order to prevent such false calculations, we had to slightly adjust the robust ROS method in R for our analyses. We decided that mean values can only be considered valid if ROS computes at most the fivefold of the detected values to lie above the detection limit. To illustrate, for a frequency band with 5% detected values, we replaced the mean value calculated by robust ROS if the 25th percentile is computed to lie above the detection limit. We replaced these erroneous values by 0.02 V/m.

Shielding of the body

Exposimeter readings can be influenced by the body of the person wearing the measurement device because the human body interacts with RF-EMF (Radon et al., 2006; Blas et al., 2007; Knafl et al., 2008). When an emitting RF source is situated frontally to the human body at a distance of 5 meters, an exposimeter placed directly on the front side of the body is not expected to measure exactly the same compared to when placed on the back side of the body. Within the QUALIFEX project, the influence of the body on exposimeter readings was investigated (Neubauer et al., 2008). In a laboratory setting, an exposimeter was carried on the back and the exposimeter readings were compared at different rotation angles of the body to the incident wave. At most rotation angles, carrying an exposimeter on the body led to an underestimation of the true field strength of 1.3 V/m (pink dashed line) (Figure 8-1 a).

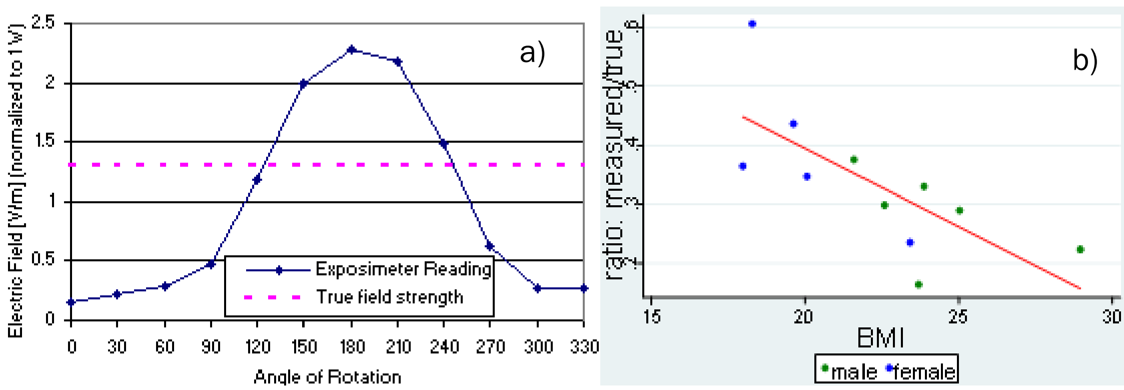

Figure 8-1: (a) Influence of the angle of the incident field (2140 MHz) when the exposimeter is carried on the back of the person and (b) influence of the body mass index (BMI) on exposimeter readings. Source: Neubauer et al., 2008.

The extent of the underestimation depends on the frequency of the exposure source as well as on the body mass index (BMI) of a person. The higher the BMI, the higher the underestimation of an exposimeter reading (Figure 8-1 b). For FM and GSM 900, the underestimation is on average about a factor of 0.5 and for W-LAN and UMTS the factor is 0.3.

Implications of measurement uncertainties on results

We found that under certain circumstances (e.g. certain slot configurations), substantial measurement uncertainties can be expected. When used in an epidemiological study, the most important prerequisite the exposimeter has to fulfil is to be able to reliably differentiate between highly and lowly exposed individuals or to produce a reliable exposure ranking between individuals. Therefore, in this context it is not essential that the exact exposure level of an individual can be perfectly determined (Heid et al., 2004). Exposimeters allow collecting several thousand measurements per person. While certain conditions may lead to an under- or overestimation of a source, these effects are found to cancel out to some degree as no systematic errors are found in the measurements taken for individual persons. For example in the UMTS uplink or GSM downlink band, measurements can be either under- or overestimated depending on the specific carrier frequency. The same is true for the isotropy if we assume that the angle of the incident wave to the device varies randomly for each measurement.

Systematic measurement errors, however, are of major concern in epidemiology (see also chapter 8.3). Such errors can for example be introduced if exposimeter readings are not stable over time. In QUALIFEX, however, this was not shown to be a substantial problem because mean exposure levels were only slightly affected by temporal calibration factors (Article 3). Another issue giving rise to systematic error is the varying measuring accuracy between different devices. Again, this effect does not seem to be crucial in our QUALIFEX project: we used eight measurement devices for the exposimeter study and included each of them as additional explanatory variable in our full exposure prediction model. None of the devices turned out to be a statistically significant explanatory variable. With regard to body shielding, the BMI of an individual might have played a role (Figure 8-1 b) and for obese persons a stronger underestimation can be expected than for individuals of less weight. We tried to overcome this problem in QUALIFEX by advising the study participants not to wear the exposimeter directly on the body but to place it close to them when not moving for a longer time period. For such situations shielding is expected to be minor. In situations where the exposimeter was carried directly on the body, for example when walking around outdoors it can be expected that shielding might have influenced our study results. A BMI-correction factor which could be used for situations when the exposimeter is worn on the body would be appealing in this context. Systematic measurement errors can also be introduced when specific exposure sources are systematically under- or overestimated. For example, exposure to GSM base stations is generally underestimated because it is not detected unless all time slots are active, and exposure to GSM mobile phones is generally overestimated, especially if only few slots are active. Again, factors to correct for this would be appealing in this context, but the determination of such correction factors is very challenging: realistic assumptions about network configurations and data traffic that represent the typical situation in the study area have to be made. Other problems are multiple signals and cross-talks between adjacent frequency bands. With regard to cross-talks, maybe one could think about developing an algorithm for cross-talks to be detected and eliminated.

Even though exposimeters can be considered the most sophisticated method available so far to assess personal exposure levels, they have some drawbacks regarding the measurement accuracy. Although systematic measurement errors can be overcome to some degree or were shown not to be very influential in QUALIFEX, it is very important to further investigate the performance of the exposimeter device. This helps to better interpret and will ideally allow us to find a way to reduce or eliminate measurement uncertainties. Similarly, the performance of devices developed in the future has to be thoroughly evaluated. For example SATIMO, the producer of the EME Spy 120, is developing a new type of personal exposimeter with a lower detection limit (0.005 V/m), an increased frequency range (80 MHz-6 GHz), a more appropriate complex signal assessment and a reduced sampling period (from 330 μs to 18 μs) which is relevant for signals with a short pulse duration (DECT, W-LAN).

8.2 RF-EMF exposure distribution in a population sample

Comparison of exposure levels in other countries

In the German study, the ESM-140 dosimeter developed by Maschek Electronics (Maschek Elecronics, Bad Wörrishofen, Germany, www.maschek.de) was used (Thomas et al., 2008a; Thomas et al., 2008b; Kühnlein et al., 2009; Thomas et al., 2010). This device is smaller than the EME Spy 120 and can be worn at the upper arm. Measurements of radio and TV bands, however, cannot be measured with the Maschek device. In addition, it has a low selectivity between the up- and downlink channels which makes it impossible to calculate mean field strengths. Therefore, exposure levels were expressed as mean percentage of the field strength of the ICNIRP reference level. Another drawback of the Maschek device is that full isotropy is only achieved when the device is carried on the upper arm and it is not suitable for RF-EMF measurements in a stand alone position. Therefore the nighttime measurements, where the study participants placed the exposimeter next to their beds, had to be excluded. In contrast to our analysis method, the authors replaced values below the detection limit (0.05 V/m) by half of the detection limit (0.025 V/m). The daytime exposure levels in 329 randomly selected adults ranged from a mean of 0.13% to a mean of 0.58% of the ICNIRP reference level (Thomas et al., 2008b). The corresponding exposure range in 1484 children and 1508 adolescents was from 0.13% to 0.92% and from 0.13% to 0.78%, respectively (Thomas et al., 2008b; Thomas et al., 2010). We found very similar values in our study population of self-selected volunteers: the exposure level to the same exposure sources during daytime ranged from 0.12% to 0.88% of the ICNIRP reference level.

In Hungary, an older version of the device (EME Spy 90) was used (Thuróczy et al., 2008). This device is unsuitable for measuring the frequency bands Tetrapol, DECT and W-LAN. Exposure was measured during 24 hours in a convenient sample of 21 participants (mostly employees of the authors' institute living in Budapest). The authors presented their results as percentage of measurements above the detection limit. This was also done in a French study, where 24h-measurements were conducted in a random population sample of 377 study participants (Viel et al., 2009a). In Table 8-1, a comparison of the proportion of measurements above the detection limit in the measured frequency bands for the three countries is given. For Switzerland, only the data from the self-selected volunteers are considered. Generally, the proportion of measurements above the detection limit is similar in all studies. In the QUALIFEX study we found a higher proportion of detected values for GSM 1800 downlink (17% compared to 5% in France). An explanation for this might be that about one forth of the study participants in France lived in rural areas, where exposure to GSM 1800 mobile phone base stations was about 4 times lower than in the urban areas (Viel et al., 2009a; Viel et al., 2009b). In QUALIFEX, only suburban and urban regions were included. Another difference is the proportion above the detection limit for the W-LAN frequency. The French authors explain this high occurrence of W-LAN in their study population with the frequent use of microwave ovens which operate in the same frequency band as W-LAN.

Table 8-1: Proportion of measurements above the detection limit (%).

	Hungary[a]	France[b]	Switzerland[c]
FM	10	11	6
TV3	0	0	1
Tetrapol	-	0	1
TV4&5	8	3	6
GSM 900 uplink	3	2	1
GSM 900 downlink	9	7	10
GSM 1800 uplink	2	4	2
GSM 1800 downlink	9	5	17
DECT	-	17	16
UMTS uplink	0	1	0
UMTS downlink	0	3	4
W-LAN	-	14	3
Total field	-	47	43

[a]From: Thuróczy et al. (2008)
[b]From: Viel et al. (2009a)
[c]Only data from self-selected volunteers

In the French measurement study, mean values were additionally calculated using the ROS method. The values were very similar compared with our data of self-selected volunteers (total exposure on average 0.20 V/m; in QUALIFEX 0.21 V/m). However, the contributions from the various sources were very different: in the

French data, FM was the main exposure contribution, followed by cordless phones, UMTS mobile phones and base stations, and W-LAN. In the Swiss data, FM and W-LAN were minor sources and the contribution of UMTS was negligible in the up- and downlink bands (0.7% and 6.7%, respectively) compared to GSM (Article 3). However, it has to be noted that the direct comparability with our data is limited: in France, ROS was applied using the values on the field strength scale, which is arguable because values on the field strength scale are not additive like the values on the power flux density scale.

In Slovenia (Valic et al., 2009), the mean exposure levels for 54 volunteers recruited by an open invitation in the media were 0.19 V/m in urban homes, 0.23 V/m at the workplace and 0.24 V/m at urban outdoor locations. The corresponding data in our study were 0.18 V/m in urban homes (for the self-selected volunteers), 0.24 V/m at the workplace and 0.28 V/m at urban outdoor locations. The values are similar; however, the comparability is again limited: In Slovenia, nondetects were replaced by the value of the lower detection limit (0.05 V/m). For frequency bands with a high proportion of non-detects this might lead to an overestimation of the field (Article 1). Therefore, it can be expected that the analysis method used for the Slovenian data led to an overestimation of the exposure levels.

The measurement study in Belgium (Joseph et al., 2008) focused on different microenvironments and was not population based. The researchers themselves performed measurements at different prespecified environments, e.g. day-rural-outdoor-cycling. 95th percentiles were calculated without using robust ROS. Sources for which the 95th percentile was below the detection limit were considered zero when calculating total exposure in a certain microenvironment. The 95th percentiles ranged from 0.16 V/m to 1.96 V/m in the different microenvironments. The highest exposures were measured during train rides, dominated by mobile phone frequencies, as observed in our data.

Generally, it is very difficult to compare exposure levels across studies due to different recruitment strategies and analysis methods. In an international cooperation we have recently finalised a paper comparing exposure levels across five different countries (Belgium, Switzerland, Hungary, Slovenia, Belgium) (Joseph et al., 2010). Mean exposure levels computed using robust ROS were compared for five microenvironments (outdoors, offices, urban homes, trains and car/bus). We found that in these specific microenvironments, exposure levels were in the same order of magnitude across the considered countries, with highest levels measured in public transport vehicles.

Compliance with reference values

A common result of all personal RF-EMF exposure measurement studies conducted until now is that exposure levels were far below the ICNIRP reference levels (Table 1-2). This is also in line with studies where stationary measurements of one or several frequency bands in the RF range were performed (Hutter et al., 2006; Keow and Radiman, 2006; Alanko and Hietanen, 2007; Bornkessel et al., 2007; Neitzke et al., 2007; Schmid et al., 2007a; Schmid et al., 2007b; Breckenkamp et al., 2008; Berg-Beckhoff et al., 2009; Joseph et al., 2009; Tomitsch et al., 2010) or where exposure from mobile phone base stations (Neitzke et al., 2007) or broadcast transmitters (Ha et al., 2007) was modelled. In a recent Turkish study, however, where exposure from 31 broadcast towers close to Ankara was modelled, the computed values were up to four times higher than the reference levels in Turkey, which are similar to the ICNIRP reference levels (Sirav and Seyhan, 2009). The only input parameters of the exposure model were the effective radiated power of the transmitters and the lateral distance to the transmitters. Topography, buildings and radiation angle were not considered. Our study, however, has shown that an appropriate geometrical description of buildings in the model region is crucial when modelling exposure from fixed site transmitters (Article 4). Objects in the line of sight such as buildings and vegetations attenuate the emitted field by orders of magnitude (Bornkessel et al., 2007). Therefore, it can be expected that these computed values were substantially overestimated.

One has to keep in mind that the low mean values resulting from exposimeter measurements do not prove that the reference values are met in every situation. There were some press responses after Article 3 was published. The “Basler Zeitung” falsely described QUALIFEX as a study which aims at verifying compliance with the reference values (BaZ, 28.10.2009). However, the distribution of electromagnetic fields is very inhomogeneous, especially inside of a room (Bornkessel et al., 2007; Neubauer et al., 2007; Knafl et al., 2008). Reference values are always related to the spatial and temporal maximum. In contrast, measurements with personal exposimeters are expected to represent an average exposure level. The difference between these two approaches is pointed out in the following example: For one participant of the exposimeter study we performed a control measurement with the NARDA SRM-3000 measurement device in order to ensure compliance with the reference values. The measured value of all three mobile phone base station frequency bands (GSM 900, GSM 1800, UMTS) was 3.1 V/m. The installation limit value is between 4 V/m (GSM 900) and 6 V/m (GSM 1800 and UMTS) (see Table 1-2). The mean value of these frequency bands measured with the exposimeter at home of the same study participant was only 0.6 V/m. Both values were below the Swiss installation limit values, however, there is a substantial difference between them.

Evaluation of the exposimeter study

Being one of the first studies assessing personal exposure using exposimeters, our data lead to a better understanding of the exposure distribution in the population in everyday life. This allows a more efficient planning of future epidemiological studies that aim at investigating health effects of RF-EMF exposure. Within the exposimeter study, we gained valuable experiences regarding the conduct of personal RF-EMF measurements with exposimeters. In collaboration with other researchers, we proposed a protocol for the conduct of personal RF-EMF measurement studies (Röösli et al., 2010).

Our study showed that combining diary data with personal RF-EMF exposure measurements is feasible. The collection of diary data was essential for our study because it allowed us to assign exposure levels and contributions from various sources to the different places and environments where people spend their time. However, filling in the diary every 10 minutes involved a large effort for the study participants. In order to reduce the effort for the study participants, we aimed at making the design of the diary easily comprehensible. Therefore, the spatial and temporal resolution was limited. We found that for the 90 second measurement interval, the 10 minute interval in the diary was a good enough resolution, even if some measurements are thereby wrongly classified (Article 3). Although very time-consuming for the study participants, collecting information on their mobile and cordless phone use was very helpful to get an idea about the impact of sources operating in close proximity of the body on the exposimeter readings. We found that the influence of such sources was quite small in our data. However, the data on cordless phone and in particular mobile phone use were not reliable for all of the study participants because some failed to write down all of their phone calls. This might have diluted our results and the actual difference between the mean values containing and excluding personal phone use might in truth be bigger.

Therefore, a more thorough evaluation on the influence of personal mobile and cordless phone use on exposimeter readings should be considered in future studies. Alternatives for collecting data on mobile phone use would be to check the stored information of the mobile phone at the end of the measurement period or to collect operator data during the measurement period. Although it was intended for the study assistant to check the mobile phone of every study participant at the end of the measurement week, this was not feasible, either because some mobile phones did not store the usage data or because of organisational problems, such as too little time when the exposimeter was handed back. Also, some people did not like it because it made them feel controlled. Collecting operator data during the measurement period is an attractive alternative because it minimizes the effort for the study participants. However, mobile phone providers must be willing to provide the data. In addition, written consent has to be obtained from all study participants. If operator data are collected, it is important to clarify if the study participant is the only user of the specific mobile phone and in which name the contract is registered (e.g. business phones) (Schüz and Johansen, 2007).

8.3 Development of an RF-EMF exposure assessment method

Our study provides important information for the conduct of epidemiological studies in the RF-EMF research field in general. We found that two basic prerequisites for conducting epidemiological studies in this research field are met: exposimeter levels are reproducible, even after several months, and considerable exposure contrasts exist between individuals (Article 3). The reproducibility of exposure levels could not be expected a priori, because RF-EMFs in our environment are highly temporally and spatially variable. We found that the main reason for this reproducibility is that residential exposure is relevant for average exposure because an individual usually spends most of his/her time at home (Mohler et al., 2009; Article 3; Article 5).

Our findings facilitate a better interpretation of the results of previous studies. We found that inexpensive and time-saving exposure assessment methods, like assessing the geo-coded distance of the residence to the closest fixed site transmitter, are in general not suitable to assess personal RF-EMF exposure. More elaborate exposure assessment methods are therefore needed.

Besides the fact that an exposure assessment method should in general reliably represent exposure, it is important to think about which type of error(s) a certain exposure assessment method might introduce when used in an epidemiological study (Heid et al., 2004). The diverse error types have varying implications for the observed exposure-outcome relationship. In this context random, systematic and Berkson errors should be mentioned. Figure 8-2 shows the error(s) that the different exposure assessment methods might introduce.

Random error can be described as the variability in the data that we cannot readily explain (Rothman, 2002). The errors of modelled or measured values are on average equal to zero because some of the values will be too high and some too low. Since an exposure assessment method is an approximation of the true exposure, random error is always involved to some degree (Figure 8-2). Random error results in an underestimation of the true effect of the exposure on the outcome.

Systematic error can be introduced because study participants might be different from individuals who do not participate in a study (selection bias) or because the information collected about or from study subjects is erroneous (information bias). All exposure assessment methods that require active participation of study participants are prone to selection bias: collecting personal measurements, spot measurements, assessing self-estimated exposure or questionnaire information for the full exposure prediction model. Selection bias is expected to be particularly pronounced if a large effort for study participants is involved, e.g. when collecting personal measurements combined with diary data. Information bias is of major concern when using self-estimated exposure and is strongly reduced if objective exposure assessment methods are used. Nevertheless, objective exposure assessment methods which disclose the aim of the study to the participants, such as collecting personal or spot measurements, can still involve information bias. When exposure is assessed using a geospatial propagation model or calculating the geo-coded distance of the residence to the closest fixed site transmitter, information bias is not at all expected to be involved because no direct information of the study participants has to be collected. A systematic error can lead to over- as well as to underestimations of true exposure-response associations.

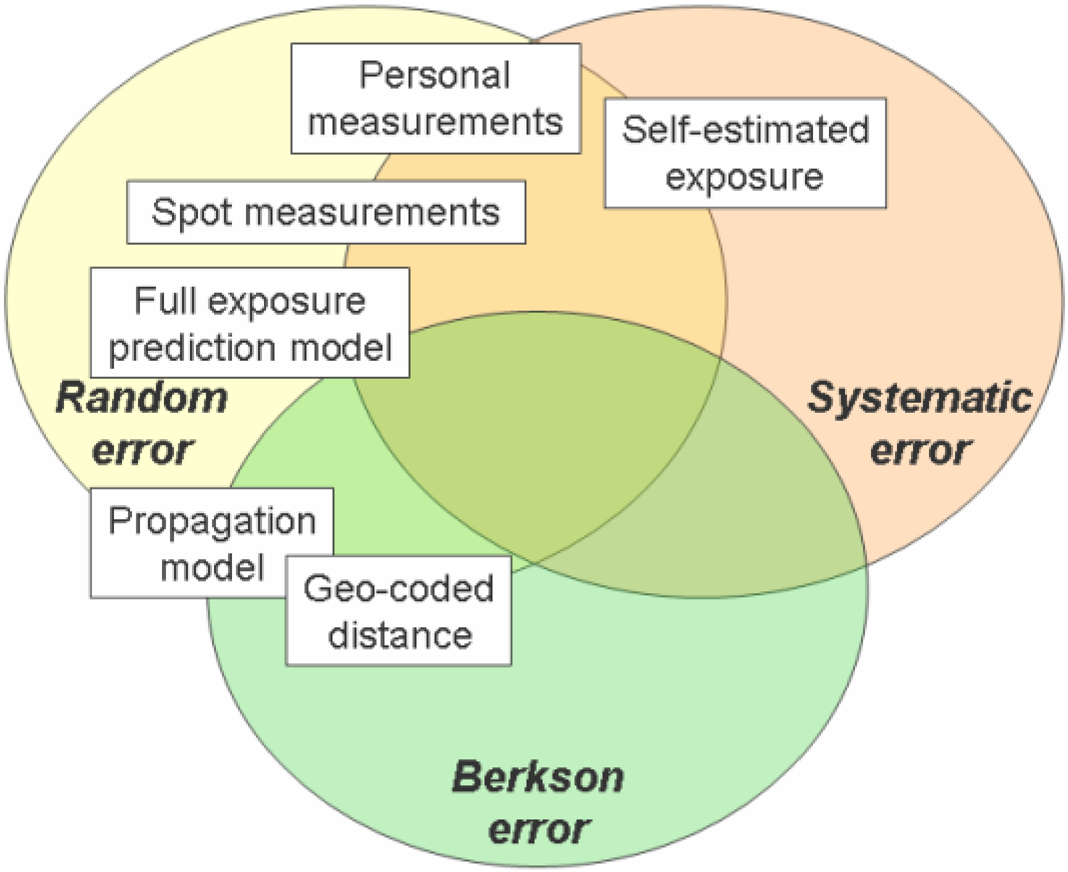

Figure 8-2: Error type(s) of the different exposure assessment methods.

Berkson error is involved when a group's average is used for each individual who belongs to the respective exposure group (Berkson, 1950; Armstrong, 1998). The following example serves as illustration for a Berkson type error: in a study investigating the association between exposure to mobile phones and headache, individuals are classified into three groups by duration of mobile phone use: <1 hour, 1-2 hours and >2 hours per week. Exposure to mobile phones, however, depends additionally on several other factors than just the duration of use. For example, the type of the mobile phone, anatomical characteristics of the head, the situation in which a mobile phone is used (e.g. in rural areas vs. in urban areas) and the network used (GSM vs. UMTS) determine exposure of an individual to his mobile phone (Erdreich et al., 2007; Vrijheid et al., 2009). Nevertheless, we can assume that exposure of all individuals in a certain group randomly varies around the mean value of this group, and that there are mean exposure differences between those three groups. The Berkson error type does not bias the exposure-outcome relationship, given that the variance is constant between the groups and the mean distribution of the errors in each group is equal to zero. However, it creates less precise estimates with larger confidence intervals and therefore reduces the power of a study. Berkson error is also involved if an exposure prediction model is applied (Armstrong, 1998). The geospatial propagation model, full exposure prediction model and geo-coded distance can introduce a Berkson type error.

Based on these considerations, minimising systematic error is most important in an epidemiological study. The two exposure assessment methods that are not expected to introduce systematic error are using a geospatial propagation model and the geo-coded distance to the closest fixed site transmitter. Unfortunately, we found very low correlations between the geo-coded distance to a transmitter and personal exposure levels. With regard to the geospatial propagation model, we found that it allows some exposure discrimination of personal exposure levels (Mohler et al., 2009; Article 6). Another advantage of using a geospatial propagation model for exposure classification is that it allows including a large study population and past exposures can be modelled if the corresponding data are available.

In QUALIFEX, we chose the approach of collecting personal measurements in a separate study collective, where no data on health were assessed. The use of exposimeters cannot be recommended in large epidemiological studies due to the high susceptibility for selection and information bias and because a large measurement study is very expensive. Exposimeter measurements could also be manipulated, e.g. by placing it right next to a RF-EMF source. Our full exposure prediction model, however, can be used in large study populations because only questionnaire data are required. Therefore, selection bias is reduced. Also, information bias is of minor concern: a very important predictor in our model is the mean value derived from the geospatial propagation model, which cannot be biased. Additional variables in the full exposure prediction model are statements about the ownership of wireless devices, which are unlikely to be heavily biased. The remaining factors are unlikely to be directly related to RF-EMF exposure by lay persons (percent FTE, the type of the house wall or window frames, amount of time spent in public transport or in cars).

Due to the difficulties and challenges we encounter when assessing personal exposure, the use of an instrumental variable as surrogate for RF-EMF exposure would be very attractive. An instrumental variable is a variable which is associated with the exposure but not with the outcome except through its association with the exposure (Greenland, 2000). Let's assume the hypothesis that RF-EMF exposure of the hypothalamus is associated with the development of sleep impairment. This exposure-outcome relationship is affected by several other variables (confounders, for example stress). In this context, a conceivable instrumental variable could be the head circumference: the larger the circumference, the farther away is the hypothalamus from the surface of the head. For two individuals with different head circumferences but the exact same mobile phone usage pattern, the hypothalamus of the person with the larger head circumference is expected to be less exposed than of the person with the smaller head circumference. As there is little evidence that there is an association between head circumference and use of mobile phones or the potential confounding variables between exposure and outcome, we could just conduct a study where we measure the head circumference of each study participant. Individuals with a large head can be considered less exposed on average than persons with a small head. The underlying error model is the Berkson model (described above in this chapter). In this case, the head circumference represents exposure of the hypothalamus, which can be obtained much easier than measuring or modelling the actual dose of RF-EMF at the hypothalamus.

8.4 Health effects of RF-EMF exposure

Our systematic review presented in Article 7 does not suggest that exposure from mobile phone base stations causes acute health effects. With regard to exposure to mobile phones, an association between the self-reported use of mobile phones and non-specific symptoms was observed in some epidemiological studies (Hocking, 1998; Chia et al., 2000; Balikci et al., 2005; Soderqvist et al., 2008). This, however, was not confirmed in provocation studies with mobile phone-like exposure (Rubin et al., 2010), except for one recent study where volunteers reported headache symptoms more often after exposure to a GSM 900 mobile phone during 3 hours than after sham exposure (Hillert et al., 2008). A recent review on the effects of RF-EMF on the human nervous system concluded that a GSM-type handset signal may result in minor effects on brain activity (van Rongen et al., 2009). However, such changes have not been found to relate to any adverse health effects so far.

While the evidence for a missing relationship between RF-EMF exposure and acute non-specific symptoms is strong based on double-blind randomised control trials (Atkins et al., 2004), no data on possible effects over longer time periods, such as over several months or years are available. Studies on long-term effects of RF-EMF exposure so far mainly focused on the association between mobile phone exposure and the development of brain tumours and other tumours of the head, e.g. of the parotid gland. The Interphone Study, an internationally coordinated case-control study involving 16 study centres in 13 countries, addressed this issue (Cardis et al., 2007). Individual national and multinational results published so far do not indicate an elevated risk of cancers in the head due to mobile phones within 10 years of first use. The results for long-term users (of more than 10 years) are inconsistent and in some studies an increased risk for certain tumour types was found (Ahlbom et al., 2009; Samkange-Zeeb and Blettner, 2009; Schüz et al., 2009). The numbers of brain tumour cases with long-term mobile phone use in these studies, however, are still too small to be informative (ICNIRP, 2009a). The pooled analysis of all national Interphone data has not been published yet.

QUALIFEX is the first cohort study where the association between RF-EMF exposure and non-specific symptoms and tinnitus after one year of exposure were investigated. We did not find that exposure to RF-EMF or change in RF-EMF exposure leads to non-specific symptoms in this time period. The cohort design used in our study is in many aspects superior to the cross-sectional design used in most previous studies and allows drawing more robust conclusions. For example, it is more suitable to take into account the temporal relationship between exposure and outcome than a cross-sectional study design. In addition, cohort studies are much less affected by information bias or exposure avoidance behaviour. In our study we tried to minimize information bias by using objective assessment methods for exposure from environmental far-field sources (geospatial propagation model, full exposure prediction model). Also, we were the first study to collect objective operator data on mobile phone use. As we had a very high follow-up rate (82%) in our study, selection bias, which is of major concern in cross-sectional analyses, is less of a problem for our cohort and change analyses.

Although in QUALIFEX we used one of the most sophisticated approach so far to study the impact of RF-EMF exposure on non-specific symptoms, there are some limitations in our study: Firstly, the development of the full exposure prediction model is based on only 166 weekly measurements. We are aware that the model is to some degree influenced by the few highly exposed individuals who were specifically selected for participation and that another study population might have yielded different results. Maybe the full exposure prediction model showed such a good performance due to our recruitment strategy to obtain a large exposure gradient. Using the model in a random population sample, as done in the main study, may result in a lower performance of the model. Secondly, we generally found very low exposure levels (on average 0.12 mW/m^2 (0.21 V/m) at baseline and 0.13 mW/m^2 (0.22 V/m) at follow-up) and also only small exposure changes over one year (ranging from -0.21 mW/m^2 to +0.18 mW/m^2). We did not find indications for a detrimental effect of RF-EMF exposure on non-specific symptoms for these low exposure levels and small changes. Our data, however, do not allow drawing conclusions about health effects which might occur at higher exposure levels (e.g. close to the reference values) or larger exposure changes. Thirdly, we may not have captured the relevant exposure metric: due to the unknown biological mechanism of RF-EMF exposure below the thermal threshold, we focused on the mean exposure level which corresponds to a cumulative exposure-response model. This is often considered the first choice in the absence of a known biological mechanism. We can currently not exclude that other exposure metrics might be more relevant like the variability of the field, peak exposure or the time spent above a certain threshold (Neutra and Del Pizzo, 2001; ICNIRP, 2009b).

Public health relevance

Assessing potential health risks from RF-EMF exposure is of public health relevance because nowadays everybody is exposed to RF-EMFs, at least to a certain degree. According to a representative survey in 2006, about 86 % of the Swiss population above 16 years own a mobile phone (ForumMobil, 2007). The number of mobile phone costumer contracts in Switzerland is steadily increasing (OFCOM, 2009) and exceeded the number of inhabitants for the first time in 2006 (FSO, 2009). In 2008, there were 8'896'706 mobile phone contracts in a population of 7'701'856 inhabitants. A similar situation is also observed in other European countries (Eurostat, 2006). The GSM network supply rate in 2008 covered 87% of Switzerland and 100% of the residential area, respectively (OFCOM, 2009). Everyone who lives in a place where mobile phone calls can be made is exposed to a background power density of around 0.001 to 10 $\mu W/m^2$ (0.002 to 0.19 V/m) at mobile phone frequencies (Schüz and Mann, 2000). Additionally, it can be expected that wireless devices will become more and more important in the future (Gati, 2009). Therefore, if there is only a small risk, the public health impact would be tremendous.

Eight percent of the participants of the QUALIFEX study consider themselves to be electrohypersensitive. Extrapolating this prevalence to the whole Swiss population older than 20 years, this results in almost 500'000 EHS individuals. In addition, 19% of the QUALIFEX study participants suspect that they developed health symptoms due to electromagnetic pollution in everyday life and 78% believe in negative health effects due to EMF. A survey with 342 general practitioners in Switzerland showed that consultations related to EMF are not uncommon: the median number of such consultations is 3 per year (Huss and Röösli, 2006). The majority of general practitioners believe that EMF can cause detrimental health effects (Leitgeb et al., 2005; Huss and Röösli, 2006; Kowall et al., 2009). Collecting subjective assessments of exposure in the QUALIFEX study offered the opportunity to investigate biological as well as psychological pathways of causality. We observed a tendency that individuals suffered more frequently from non-specific symptoms if they believe to be subject to higher exposure as compared to the Swiss population (Article 9). A possible explanation that health problems due to EMF exist in our society is the nocebo effect (concerns regarding negative effects lead to health impairment). This effect was observed or at least assumed to play an important role in several studies performed so far (Altpeter et al., 2006; Röösli, 2008; Stovner et al., 2008; Rubin et al., 2010). This means that health problems due to EMF are possibly caused by psychological but not biophysical effects. Nevertheless, this leads to an additional burden of disease in our society.

This thesis provides new insights into possible health effects of RF-EMF after prolonged exposure periods in the low dose range. Such knowledge is important to evaluate the risk for the general population and contributes to a more informed debate. In Switzerland, the erection of new mobile phone base stations faces increasingly fierce opposition from the exposed population resulting in costly and ineffective decision processes. Although for some persons exposure to mobile phone base stations can be an important exposure contribution, our data demonstrate that it is in general not justified to only consider mobile phone base stations because other sources may be just as relevant or even more relevant exposure sources in our daily life.

Due to the fact that at this point we cannot exclude that RF-EMFs cause detrimental effects in the long run, from a scientific point of view the precautionary approach should be maintained. Although we found that exposure from fixed site transmitters at home is important in terms of the total exposure to environmental far-field sources (Mohler et al., 2009), this does not mean that one is not able to control his or her own exposure. Especially when considering the local exposure on the head caused by the use of close to body sources, personal devices can be responsible for a substantial part of personal exposure. Therefore, a considerable exposure reduction can be reached by minimising the use of body-close sources and to prefer wired over wireless solutions, such as using conventional phones instead of cordless phones or using a LAN cable instead of Wireless LAN. Moreover, cordless phones with a so-called ECO-mode are nowadays available, which means that the base station of the cordless phone only radiates when a phone call is made. Using hands-free kits for mobile phones generally leads to a lower exposure in the head area (Kühn et al., 2009). The precautionary principle should in particular be applied to children. Children might be more sensitive to RF-EMFs because of a greater susceptibility of their developing nervous system. Furthermore, today's children and adolescents are expected to have a higher cumulative exposure throughout their life than today's adults, because they start using wireless devices earlier in life

(Kheifets et al., 2005; Leitgeb, 2008). In addition, there are indications that higher SAR values for children in comparison to adults occur from far-field sources as well as from the use of mobile phones (de Salles et al., 2006; Wiart et al., 2008; Joseph et al., 2010). Until now, only few epidemiological studies have investigated a possible association between exposure to RF-EMFs and health outcomes in children and adolescents (SCENIHR, 2009).

8.5 Outlook

In a next step, we will evaluate the generalisability of the full exposure prediction model developed in the framework of the QUALIFEX project. This will be done in a different study region, more precisely in the six cantons of central Switzerland (Lucerne, Nidwalden, Obwalden, Schwyz, Uri and Zug). For this region we have also developed a geospatial propagation model for fixed site transmitters (E-smog Messung: www.e-smogmessung.ch). We will conduct weekly exposimeter measurements in about 100 volunteers. This will allow us to evaluate the performance of the full exposure prediction model in another context.

Due to the fact that personal exposure measurement devices have only recently become available, the conduct of further personal measurement studies is strongly encouraged. More information has to be collected on the spatial and temporal exposure distribution as well as on exposure levels. A better knowledge of the exposure levels in different microenvironments and of the determinants of personal exposure is crucial for health risk assessment. In particular, more data on personal exposure of children should be collected.

It would be interesting to investigate the effects of RF-EMF on health based on the actual absorption (SAR) of RF-EMF by the human body, because it varies for different frequency bands. For similar RF exposure intensities, the body absorbs about five times more of the RF energy from FM radio and television frequencies (around 100 MHz) than from base station frequencies (around 1 to 2 GHz) (Valberg et al., 2007). In our analyses, we defined exposure as the field strength measured close to the human body. In collaboration with the group of Jürg Fröhlich from the Swiss Federal Institute of Technology Zürich (ETH) we are currently investigating the relative contributions of sources close to the body and environmental far-field exposure in terms of the whole-body SAR. Preliminary analyses show that whole-body SAR for an average mobile phone user (25.6 minutes per week) owning a GSM mobile phone is dominated by the personal mobile phone. However, when using a UMTS phone, which radiates about 100-500 times less than a GSM mobile phone (Gati et al., 2009), exposure to environmental far-field sources features the dominant contribution to whole-body SAR (Lauer et al., 2010).

One has to keep in mind that our findings reflect the momentary situation. Since the technical development is very quick, a change in the exposure situation of the population can be expected. Features of future technologies are large bandwidths, adaptive power control and the transmission of high data rates (Gati, 2009). The fourth generation of mobile broadband standard, LTE (long term evaluation), is currently being developed. First investigations demonstrated that LTE will lead to similar exposure as 2G and 3G networks. As long as such new sources do not replace former technologies but are simultaneously operated, this will lead to an increase of environmental RF-EMF exposure. Additionally, multifunctional smart devices operating in close proximity of the body will possibly be used more intensively. Exposure assessment will probably become more and more complicated in the future. For instance, new technologies will use a beamforming signal processing technique. Beamforming allows controlling and changing the directionality of the reception or transmission of a signal on a transducer array. This will introduce a new degree of uncertainty in the already complex RF-EMF exposure assessment.

QUALIFEX was the first study to investigate the association between exposure to different RF-EMF sources in everyday life and non-specific symptoms in a cohort design. In addition, we were the first to use a comprehensive exposure assessment method including objective data on both, exposure to environmental far-field and close to body sources. Our results therefore allow us to draw more robust conclusions in comparison to previous research. We did not find an impact of RF-EMF exposure on non-specific symptoms. Still, we cannot exclude the presence of an effect, especially at higher levels close to the reference values or due to higher exposure changes than experienced today. Therefore, further studies on long-term effects due to RF-EMF exposure should be conducted. Future studies should put an effort in developing reliable exposure assessment methods. The quality of the exposure assessment determines in a large part the validity of an epidemiological study as well as the result of risk quantifications. Our study has thoroughly evaluated different exposure assessment methods and the systematic approach used in QUALIFEX can be used as guideline for future epidemiological RF-EMF research.

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Curriculum vitae

Name	Patrizia Frei
Date of birth	29. October 1981
Nationality	Swiss

Education

1889 – 1994	Primary school in Eggersriet, SG
1994 – 1996	Secondary school in St. Gallen
1996 – 2001	High school in St. Gallen, Matura Typ B (latin), including a one semester student exchange in Porrentruy, JU (1999)
2001 – 2006	Swiss Federal Institute of Technology Zurich (ETHZ): Basic studies in environmental sciences, special studies in human-environment-systems and biomedicine. Master thesis on the subject of allergies and epidemiology
2007 – 2010	PhD in Epidemiology at the Institute of Social and Preventive Medicine (ISPM) in Bern and the Swiss Tropical and Public Health Institute Basel (Swiss TPH)

Further training:

2007-2009	Advanced methods in epidemiology: applied regression modelling, University of Bern (lecturer: J. Sterne), 2 ECTS
	NISV Messtechnik-Seminar (lecturer: M. Wuschek), Emitec AG, Rotkreuz, 2 days
	Fragebogen- und Interviewkonstruktion: Entwerfen und Durchführen von Befragungen in Medizin und Gesundheitswissenschaften, University of Zürich (lecturer: U. Frick), 1.5 ECTS
	Biostatistik IIa: Regression, University of Bern (lecturer: C. Schindler), 2 ECTS
	Writing a journal article and getting it published, University of Bern (lecturers: N. Law, M. Egger), 1 ECTS
	Book Club/Seminar: Epidemiology, University of Bern (lecturer: C. Kühni), 3 ECTS

4th course of the International School of Bioelectromagnetism (EBEA) “Electromagnetic fields and Epidemiology”, Erice (I) (lecturers: S. Lagorio, J. Schüz et al.), 7 days

Multilevel analysis, University of Bern (lecturers: M. Röösli, G. Michel), 1 ECTS

SSPH+ Summer School: Policy and practice of screening, University of Lugano (lecturer: F. Paccaud), 1 ECTS

Statistical methods for epidemiology, revisited, University of Bern (lecturer: T. Lash), 1 ECTS

Mixed methods research and evaluation, University of Basel (lecturer: M. Bergman), 1 ECTS

Observational epidemiological studies: advanced methods for design and analysis, University of Basel (lecturers: J. Schwartz, M. Röösli), 2 ECTS

Working experience

2004-2005	Assistant at the Institute of Integrative Biology, ETH Zürich
2004-2005	Internship at the Swiss Federal Laboratories for Materials Testing and Research (EMPA), Technology and Society Lab, St. Gallen

List of Publications

Röösli, M., Frei, P., Mohler, E., Braun-Fahrländer, C., Bürgi, A., Fröhlich, J., Neubauer, G., Theis, G., Egger, M., 2008. Statistical analysis of personal radiofrequency electromagnetic field measurements with nondetects. Bioelectromagnetics 29(6): 471-478.

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Mohler, E., Frei, P., Aydin, D., Bürgi, A., Röösli, M., 2009. Persönliche Exposition durch hochfrequente elektromagnetische Felder in der Region Basel (Schweiz): Ein Überblick über die QUALIFEX-Studie. Umweltmedizin in Forschung und Praxis 14(6): 329-338.

Bürgi, A., Frei, P., Theis, G., Mohler, E., Braun-Fahrländer, C., Fröhlich, J., Neubauer, G., Egger, M., Röösli, M., 2010. A model for radiofrequency electromagnetic fields at outdoor and indoor locations for use in an epidemiological study. Bioelectromagnetics 31: 226-236.

Frei, P., Mohler, E., Bürgi, A., Neubauer, G., Fröhlich, J., Braun-Fahrländer, C., Röösli, M., 2010. Classification of personal exposure to radio frequency electromagnetic fields (RF-EMF) for epidemiological research: Evaluation of different exposure assessment methods. Environ Int 36(7): 714-720.

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Joseph, W.,* Frei, P.,* Röösli, M., Thuróczy, G., Gajsek, P., Trcek, T., Bolte, J., Vermeeren, G., Mohler, E., Juhász, P., Finta, V., Martens, L., 2010. Comparison of personal radio frequency electromagnetic field exposure in different urban areas across Europe. Environmental Research, in press. DOI: 10.1016/j.envres.2010.06.009. *both authors contributed equally

Mohler, E., Frei, P., Braun-Fahrländer, C., Fröhlich, J., Neubauer, G., Röösli, M., 2010. Effects of everyday radio frequency electromagnetic field exposure on sleep quality: a cross-sectional study. Radiation Research, in press. DOI: 10.1667/RR2153.1.

Röösli, M., Frei, P., Mohler, E., Hug, K., 2010. Systematic review on the health effects of radiofrequency electromagnetic field exposure from mobile phone base stations. Bulletin of the World Health Organization, in press.

Frei, P., Mohler, E., Neubauer, G., Fröhlich, J., Braun-Fahrländer, C., Röösli, M., QUALIFEX-team. Cohort study on the effects of radio frequency electromagnetic field exposure in everyday life on non-specific symptoms of ill health and tinnitus. submitted.

Lauer, O., Neubauer, G., Röösli, M., Riederer, M., Mohler, E., Frei, P., Fröhlich, J. Reliable assessment of the measurement accuracy of band-selective personal exposure meters: an example study. submitted.

Röösli, M., Mohler, E., Frei, P. Sense and sensibility in the context of radiofrequency electromagnetic field exposure. submitted.

Conference Contributions

29.06.2007	Monitoring von elektromagnetischen Feldern: Überprüfung von Tagebucheinträgen mittels Messwerten Presentation at the Ambulatory Assessment Conference, Fribourg
27.11.2007	Individual exposure to radio frequency electromagnetic fields: preliminary results from QUALIFEX Frei, P., Braun-Fahrländer, C., Bürgi, A., Egger, M., Fröhlich, J., Joos, N., Neubauer, G., Theis, G., Röösli, M. Abstract and presentation, CEEC ISEE (Eastern European Chapter of the International Society for Environmental Epidemiology) Conference, Czech Republic
16.10.2008	Personal radio frequency electromagnetic field exposure in a Swiss population sample P. Frei, E. Mohler, C. Braun-Fahrländer, A. Bürgi, M. Egger, J. Fröhlich, N. Joos, G. Neubauer, G. Theis, M. Röösli Abstract and presentation, ISEE ISEA (International Society for Environmental Epidemiology & International Society of Exposure Analysis) Conference, Pasadena, USA
19.06.2009	A predictive model for personal RF-EMF exposure P. Frei, E. Mohler, A. Bürgi, G. Neubauer, A. Hettich, G. Theis, J. Fröhlich, C. Braun-Fahrländer, M. Egger, M. Röösli Abstract and presentation, BEMS (Bioelectromagnetics Society) Conference, Davos

Invited Presentations

07.04.2007	Background and methods of the QUALIFEX project Presentation at a colloquium at the Institute of Social and Preventive Medicine, University of Basel
16.10.2007	QUALIFEX: Gesundheitsbezogene Lebensqualität und Exposition gegenüber hochfrequenten elektromagnetischen Feldern: eine prospektive Kohortenstudie Presentation at the “Fachtagung Strahlenschutz” at Novartis, Basel

04./06.11.2009 RF-EMF exposure assessment in the Swiss QUALIFEX study/ Challenges in assessing RF-EMF exposure: An epidemiological perspective

Presentations at the COST BM 0704 (European Cooperation in Science and Technology) meeting in Paris, France

10.03.2010 Individual exposure to RF-EMF: the Swiss QUALIFEX study

Presentation at a colloquium at the Institute of Cancer Epidemiology at the Danish Cancer Society, Copenhagen, Denmark

Awards and Grants

Award for the forth best scientific paper presented in the platform competition at the joint meeting of the Bioelectromagnetics Society and the European BioElectromagnetics Association 2009.

Grant from the COST BM 0704 (European Cooperation in Science and Technology) for a short-term scientific mission at the Institute of Cancer Epidemiology, Copenhagen.