CHALLENGES AND ADVANCEMENTS IN RADIOFREQUENCY ELECTROMAGNETIC FIELDS EXPOSURE ASSESSMENT FOR ENVIRONMENTAL EPIDEMIOLOGY

Luuk van Wel

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Uitdagingen en ontwikkelingen in radiofrequente elektromagnetische velden blootstellingsbeoordeling voor de milieu-epidemiologie

(met een samenvatting in het Nederlands)

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Contents

CHAPTER 1

General introduction

Life without smartphones, tablets, and other mobile communication devices has become difficult to imagine. The past decades have seen a large increase in mobile communication device ownership, of which the modern smartphone is a prime example (1). These devices are being used for many tasks, ranging from making traditional voice calls to handling online banking transactions. In order to function, mobile communication devices require a constant exchange of information which is achieved using radiofrequency electromagnetic fields (RF-EMF). Consequently, the rise of mobile communication device use has led to a near continuous exposure to RF-EMF in modern society. This has not gone unnoticed, with concerns being raised about potential health effects related to RF-EMF exposure (2-5). To address these concerns an accurate and biologically relevant exposure assessment is required. This has turned out to be a challenging effort as RF-EMF exposure tends to be highly spatially and temporally variable. In addition, it is dependent on individual behaviour. This thesis highlights the challenges of RF-EMF exposure assessment while applying novel methodologies for integrative individual exposure assessment.

Radiofrequency electromagnetic fields

Electromagnetic fields can be visualised as waves traveling outwards from a source at the speed of light. These waves are characterised by the number of times they oscillate per second, expressed as the frequency (in Hz), and their wavelength (in metres). The frequency and wavelength are inversely correlated: the higher the frequency, the shorter the wavelength. This can be seen in Figure 1.1.

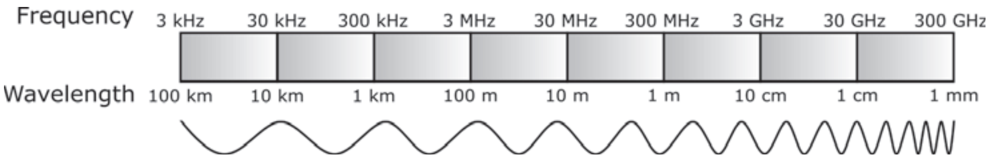

Figure 1.1: The radiofrequency electromagnetic spectrum.

The energy contained in the wave remains constant, but as the wave spreads out in all directions from its source the energy is spread out accordingly and the amount of energy on each spot covered by the wave decreases. Think of this as a ripple in a big pond, where the ripple decreases in size as it spreads out from its origin. When talking about RF-EMF sources, a distinction is usually

Table 1.1: Frequencies and wavelengths of some radiofrequency communication networks.

RF source[a]	Frequency (MHz)	Wavelength (cm)
FM radio	88 – 108	340 – 280
DVB-T (television)	470 – 790	64 – 38
GSM 900; UMTS; LTE; 5G	880 – 960	34 – 31
GSM 1800; UMTS; LTE	1710 – 1880	18 – 16
DECT (cordless phones)	1880 – 1900	16 – 16
UMTS; LTE	1920 – 2170	15 – 14
WiFi 2.4 GHz	2400 – 2485	12 – 12
LTE	2500 – 2690	12 – 11
WiFi 5.8 GHz	5150 – 5875	6 – 5

[a] The network type using a frequency band may vary between countries and over time with the introduction of new technologies.

made between sources in the near-field and in the far-field regions. The near-field region is generally defined as the area less than one wavelength away from the antenna, whereas the far-field is generally seen as two to three wavelengths away. As can be seen in Figure 1.1, the size of the near-field depends on the frequency at which the RF source is transmitting: it can mean centimetres, or multiple metres away. Table 1.1 provides some examples of frequencies and wavelengths used in communication networks.

Energy

The amount of energy carried by an electromagnetic wave is proportional to its frequency, with higher frequency waves having higher energy levels. The electromagnetic spectrum can be divided into categories using frequency ranges, with low energy, extremely low frequency (ELF) fields on one side, and high energy gamma rays on the other side. This thesis focuses on frequencies used for mobile communication networks, the so-called radiofrequency (RF) electromagnetic fields (EMF). This category ranges from 3 kHz to 300 GHz (Figure 1.1). The amount of energy, or the field intensity, is expressed in Volts per metre (V/m). Alternatively, power density is used at higher frequencies, expressed in Watts per metre squared (W/m^2). The units can be converted to each other using the formula:

$$V/m = \sqrt{W/m^2 * 377}$$

Energy absorbed by the human body when exposed to an RF field is expressed by the specific absorption rate (SAR), in Watt per kilogram (W/kg). Where V/m and W/m^2 can be used to express the energy exposed to at skin level, SAR relates to the amount of energy that is absorbed at the anatomical site of interest, for example the brain. In short, the exposure at the anatomical site of interest is not only dependent on RF source characteristics such as transmission power and frequency, but also characteristics of the subject, including age, body type, and clothing.

Modulation

An electromagnetic wave in itself carries little information that we are interested in (e.g., speech or data information). Some form of encoding has to be performed to include the information we wish to transfer into the electromagnetic wave. This is achieved using modulation: imposing an input signal onto a carrier wave. There are many different modulation schemes. A simple example is frequency modulation (FM), used for radio broadcasting. The frequency is lowered or raised slightly to encode the radio broadcast. Each modern communication technology (e.g., GSM, WiFi, LTE) uses its own modulation and consequently has a different wave, even when using the same frequency.

RF-EMF exposure in epidemiological studies

In epidemiological studies we are interested in the amount of energy, either at skin level or absorbed at the relevant anatomical site. Each transmitting RF source will result in some amount of exposure. The exposure from one source may be very little, however the combined exposure from many RF sources around a subject may be substantial. For individual exposure assessment in epidemiological studies we would like to know the combined dose (amount of energy) from all relevant sources. A so called integrative individual exposure assessment, integrating the dose from all relevant sources into a single, combined dose. By using the amount of energy received from RF-EMF sources as the exposure variable of interest, we assume that modulation and frequency of the signal do not strengthen or weaken the effect of the energy received.

Developments in RF sources and technology

Wireless methods aimed at transmitting information have been around for quite some time. Frequency modulation (FM) broadcasting has been used commercially since the late 1930s and FM radio stations are still around today, using the

88 – 108 MHz frequency range. In 1979 the first commercial mobile telecommunications network generation was introduced in Japan, 1G. It was based on a cellular radio system, where an area is divided into cells. Each cell is served by a radio base station, which receives data from the mobile device (i.e.: uplink) and sends data back to the mobile device (i.e.: downlink). Like FM broadcasting, the first generation network was an analog telecommunication standard.

The second generation, or 2G, was introduced in 1991. An important difference with the previous generation was that these standards used digital encoding rather than analog transmissions, being much more efficient with the frequencies available for communication. Along with phone calls, other uses such as text messages (SMS) and multimedia messages (MMS) became possible. A further development of the 2G system introduced data networks, allowing for early internet access on mobile phones. In the late 1980s, early 1990s, another standard was introduced, the Digital Enhanced Telecommunications (DECT), primarily used for cordless telephone systems. Today, most cordless landline phones in homes still use this technology.

With the rise of the global internet and increasing demands for mobile data use, the third generation network standards (3G) were introduced in the early 2000s along with the first smartphones. Smartphones were not only used for phone calls or text messages but could be used for functions such as reading e-mails or browsing the internet, where data rather than voice calls needed to be transmitted. Tablets became popular as well around this time, requiring wireless communication to receive or transmit data. This was achieved either by including a SIM-card in these devices to access 3G networks, or via WiFi networks. WiFi is a standard for wireless local area networks (WLANs), introduced in the late 1990s as a wireless alternative for high-speed cable connections and is typically used with hotspots each covering a range of about 20 to 30 metres. Around the same time the first Bluetooth-enabled devices became available. Bluetooth is a protocol for short range, low power consumption communication in the personal area network (PAN), well known examples include wireless headsets used during phone calls.

Meanwhile the evolution of cellular networks continued as the need for fast data throughput increases with functions such as streaming movies or making video calls. As a result, the fourth generation cellular network, 4G, was introduced in 2009. WiFi made similar advances, introducing 5GHz networks using higher frequencies. The number of devices using some form of wireless communication increased as well. Medical sensors transmitting their measurements in real-time, smartwatches and fitness trackers continuously keeping a low-level data

connection open between the device at the user's wrist and their smartphone somewhere nearby. Rapid development in sensor technology, low-powered integrated circuits, and wireless communication enabled the creation of body area networks (BAN), encompassing devices on the skin and even inside the body.
Currently the fifth generation (5G) of cellular networks are being deployed. Besides an improvement in data throughput, 5G networks offer low latency (i.e.: be more responsive) and the ability to connect many devices simultaneously. Compared to previous generations, new technologies used include massive MIMO (multiple input and multiple output) antennas for increased capacity and beamforming, where radio waves are more focused towards the target device. The frequency ranges used will be higher than previous generations, with the so-called frequency range 2 moving above 24 GHz. These changes provide new challenges for RF-EMF exposure assessment as measurement devices and models will need to be adjusted or even recreated entirely to take the changes into account.

Effects on exposure assessment efforts

For RF-EMF exposure assessment, these technological advances meant that new changes had to be taken into account with each new network generation. A device can transfer one unit of information (i.e.: calls or data) for one unit of energy. The amount of information sent per unit of energy depends on the network technology used. But it holds true for each technology that the transmission of larger quantities of data requires larger amounts of transmission energy. Not only has the amount of RF-EMF use greatly increased as a result of higher data needs, the types of devices, their functions, and the way they are being held relative towards the body of the user have also changed.
In the early days, FM radio broadcasting networks and early cellular networks were the main sources in the far-field area contributing to RF-EMF dose, where mobile phones were the main sources contributing in the near-field. Devices were typically held close to the head, and as such the brain was a likely anatomical site for potential health concerns caused by RF-EMF exposure. Users could be asked how often and how long they used a device on average. With the advent of newer networks and device functions, uses such as texting and browsing meant that the phone was no longer held exclusively near the head. Not only that, but the transmission of text messages required much less transfer of information than a voice call, which consequently resulted in a lower RF-EMF exposure to the head from messages compared to calls as less data had to be

transmitted.
The introduction of one technology did not necessarily mean the disappearance of another, with FM broadcasting, DECT devices, WiFi, and second through fifth generation networks co-existing simultaneously. Each technology is assigned its own frequency range, resulting in a more intensive use of the electromagnetic spectrum and the requirement of including all these frequency ranges in exposure assessments. Lastly, new devices other than mobile phones were making use of these networks, requiring epidemiological and exposure assessment studies to ask for more than just mobile and DECT phone use: how often did someone use their fitness tracker, is their laptop regularly connected via WiFi? And do they know whether they are using a medical sensor capable of transmitting its findings in real-time or whether their new virtual reality headset transmits at 5 GHz or at 60 GHz?

The RF-EMF exposure assessment challenge for epidemiological studies

Questionnaires, operator data and SMPs

Early epidemiological investigations into RF-EMF exposure used questionnaires to gain insight into frequency and duration of mobile phone and DECT phone use, as these were the main and few sources at the time. With voice calls being the primary use of early mobile phones and of DECT phones, this generally covered most of the use time. When recalling phone use however, errors were introduced in the form of recall bias: a subject either under- or overestimating their actual use (6). In case-control studies, where cases with a disease of interest (e.g., malignant brain tumour) are compared to healthy controls, differential recall error might even occur. With this type of recall bias, the error of the cases differs from the controls. An alternative for asking subjects about their use was to request the call records from mobile phone network operators, the operator data. Downsides included the records often being incomplete (when based on billing records they would only contain outgoing calls), and it not always being clear who the actual user of the phone was when making the calls when a device was being shared between users (7,8). With the introduction of smartphones, it became possible to install monitoring applications, resulting in software modified phones (SMPs). SMPs are capable of recording not only the voice calls made and received, but also text message statistics, data traffic and even how the device was held during calls (9,10). The additional information collected allowed for better exposure estimation in epidemiological studies (e.g., was the phone near the head while transmitting data).

Transmission power

While these solutions worked for improving the quality of frequency and duration of voice call estimations, information on actual levels of RF-EMF exposure remained lacking. As mentioned previously, the level of RF-EMF exposure originating from a source depends on the transmission power that was needed to successfully transfer the information. A phone call made inside a concrete building will require a higher transmission power (thus increasing RF-EMF exposure) to send a signal back to the base station than a phone call outside in clear weather. Conversely, a phone call transmitted on a third-generation network requires generally less power than a second-generation network call thanks to improved power regulation in the newer 3G technologies. In short, we need to know not only the quantity of use, but also the transmission power.

Novel uses and source positions

With the ongoing evolution of mobile communication networks, novel uses (i.e.: mobile internet access) became commonplace. This resulted in new ways of holding the device relative to the body (users generally do not browse the internet with the device against their head) and new data use patterns. Where previously an average transmission power could be applied over the use time, potentially stratified per network type, this was no longer possible with many different uses. A phone call could result in more intensive information transmission than simply sending e-mails. In order to take these uses into accounts, they had to be included in epidemiological surveys, asking participants for their average use frequency and duration of many functions. To further complicate matters, different uses meant different positions at which the device was held, and when investigating the brain as anatomical site for potential health effects, a mobile phone held directly against the head would result in different exposure levels (both in magnitude and area of exposure) compared to a mobile phone held in front of the body. New devices were introduced as well: Bluetooth headsets allowed for phone calls taking place with the source (i.e. the mobile phone) being in a pocket, or even on a table up to a few metres away from the body while simultaneously adding a negligible amount of RF-EMF exposure to the head from

data transmission using Bluetooth communications. Tablets could be used for many functions that a smartphone could do, but were often held differently.
More recently health trackers worn around the wrist using Bluetooth communications, or virtual reality glasses using WiFi or mobile phone networks can be added to the list of RF-EMF sources. For a questionnaire-oriented approach subjects would have to recall which devices they used, which functions they used those devices for, the location during that use, and the duration of use for each combination. As a result, the likelihood of recall bias and uncertainty will most likely increase.

Exposure monitors

Rather than asking users about their mobile device use, RF-EMF exposure monitors can be used: devices measuring exposure on multiple commonly used frequency bands. These devices often include 14 to 16 distinct frequency bands (11,12). For cellular networks a distinction is made between uplink (i.e.: transmission from a device towards a cellular base station) and downlink (i.e.: transmission from the cellular base station towards a device) frequency bands. Measured uplink can be from the user's own devices, or from a nearby device where the exposure monitor happens to be in the path between a transmitting device and the targeted cellular base station. This example also holds true for downlink, where the signal originating from the cellular tower is not necessarily aimed at a device nearby the exposure monitor.
An exposure monitor could either be used for spot measurements in homes, schools, and workplaces or given to an individual to wear for a certain amount of time. There are significant measurement uncertainties involved however, caused by so called crosstalk where frequency bands are difficult to separate (13,14), by the location where the exposure monitor is worn due to body shielding (15), and the highly spatially and temporally variable nature of RF-EMF exposure resulting in an exposure pattern with many peaks and moments where the signal drops below the detection limits of the exposure meters causing statistical challenges in analysing the results (16). In addition, the exposure meters used in epidemiological studies are usually calibrated for far-field sources. Still, measuring RF-EMF exposure this way allows for the inclusion of many sources, including far-field sources such as FM broadcasting and cellular base stations, sources which cannot or can hardly be captured using a questionnaire-based approach.

Modelling exposure

Rather than exposure monitors, deterministic physical models can be used for both near-field and far-field sources. Both questionnaire and mobile phone operator records can be used as input for dose estimation models (17,18). For far-field exposures, wave propagation models such as NISMAP can model the exposure resulting from base stations with reasonable accuracy using antenna position, transmission power, and building heights (19,20). Inaccuracies and gaps in the exact antenna and receptor positions are responsible for much of the uncertainty in these approaches. Other sources of inaccuracy include shielding, reflections of beams on facades, and issues with transmission power estimations: should an average transmission power be assumed, how are subjects moving around rather than staying in one location taken into account, and how do you take daily differences such as time of day and atmospheric conditions into account.

Other influencing factors

Interindividual differences are also of concern. Assuming we can accurately assess RF-EMF exposure at the skin level, we need to know which part of that reaches the anatomical site of interest. (e.g., the brain when the relevant outcome is the occurrence of brain malignancies). This depends on many factors, including age, sex, skull thickness, amount of adipose tissue, and shielding from clothing or other items on the body.

Time-sensitive health outcomes

The time at which a potential health outcome is assessed in epidemiological studies can be critical when looking at short-term transient health effects. A study exploring malignant brain tumours as a potential health outcome can generally aggregate RF-EMF exposure levels per month, year or longer as this health outcome takes a long time to develop. Conversely, short-term effects such as headaches or disorientation require a health outcome assessment (e.g., asking questions concerning wellbeing) as soon as the exposure takes place. This is generally not possible without an exposure monitor relaying real-time exposure information to a platform or interviewer capable of performing the assessment.

Data quality

Summarizing, there are many factors that need to be taken into account when assessing RF-EMF exposure. High quality information is needed on the following factors:

1. All mobile communication devices used in the near-field, and for each device:
   (a) Frequency and duration of use
   (b) Functions used
   (c) Amount of data transfer needed for each function
   (d) Where the device was held in relation to the body during use
   (e) Network type and frequency (Hz) used
2. Nearby mobile communication devices not directly being used, but connected and active
3. For far-field sources either exposure monitor measurements or location history should be acquired for modelling
4. Personal characteristics when determining energy absorbed at the target site:
   (a) Age, sex, BMI

The above information is often not available for one single source (e.g., mobile phone use), let alone for multiple sources nearby and further away from the subject. For improved (individual) exposure assessment, an integrative exposure effort is necessary where data from questionnaires, measurements, and modelling efforts is combined to include all relevant RF-EMF sources. Depending on the transient nature of the health outcome under investigation, the exposure assessment might need to be modelled or measured at varying timescales.

Aim

The overall aim of this thesis is to explore the challenges in RF-EMF exposure assessment and to come to improved (integrative) individual exposure assessment methodologies using the insights gained.

Thesis outline

Chapter 2 describes a series of RF-EMF spot measurements in Amsterdam primary schools to gain insight in far-field exposures of children at schools and to identify challenges involving RF-EMF measurements. **Chapter 3** provides further insight into the systematic and random errors due to mobile phone use recall. Data from the MOBI-Kids study is used to compare recall of cases with a brain tumour diagnosis with that of healthy controls, assessing whether there is evidence of differential recall errors. Data includes interviews on mobile phone use and mobile phone operator records. In **Chapter 4** recall bias is investigated using software modified phones (SMPs) rather than mobile phone operator records. The next two chapters describe two novel methodologies for assessing RF-EMF exposure. **Chapter 5** describes an integrative exposure metric, modelling RF-EMF dose from both near and far-field sources for different anatomical sites using both questionnaire information and measurement data. **Chapter 6** describes a context-sensitive ecological momentary assessment (CS-EMA) approach, where an exposure monitor is linked with a smartphone platform to monitor exposure levels in real-time and to perform wellbeing assessments triggered by real-time exposure levels. **Chapter 7** discusses the main findings, benefits and drawbacks of various exposure assessment approaches, and provides an outlook on future RF-EMF exposure assessment concerning upcoming technological innovations.

1

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CHAPTER 2

Radiofrequency exposure levels in Amsterdam schools

Luuk van Wel, Roel Vermeulen, Manon van Eijsden, Tanja Vrijkotte,
Hans Kromhout, Anke Huss.

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Abstract

There is limited knowledge of children's exposure to radiofrequency electromagnetic fields (RF-EMF). As they spend a considerable proportion of their time in schools, assessing exposure in schools will contribute to more accurate knowledge regarding RF-EMF exposure of for children. This study assessed indoor RF-EMF levels in 102 primary schools in Amsterdam, the Netherlands. Spot measurements were generally taken in two classrooms per school building on the same day using a device capable of measuring 14 different frequency bands. Average power density across all schools was 70.5 μW m^{-2}, with little over half (56.3%) originating from outdoor sources. Overall low RF-EMF levels were found with mobile phone downlink and DECT signals being the main contributors to total average power density.

Introduction

The use of wireless communication devices has rapidly increased in modern society. Existing mobile phone networks are continuously being expanded to facilitate the growing demand for wireless communication, while simultaneously novel technologies are being introduced. Adults as well as children are using (smart)phones, tablets, and other devices on a daily basis (1). The increase in use of wireless communication devices leads to an increase in the number of people exposed to radiofrequency electromagnetic fields (RF-EMF). Wireless local area networks (WLAN) based on WiFi technology are gaining popularity in schools, where devices such as tablets and laptops are being introduced as educational tools. Information on RF-EMF exposure of children in schools is sparse with studies mostly sampling a limited number of school locations (2-6). The objective of our study was to assess indoor RF-EMF levels to which children are exposed in a large number of primary schools in Amsterdam.

Methods

Measurements were taken at 102 out of 213 primary schools in the Amsterdam area, the Netherlands, between July 2011 and July 2012 (Figure S2.1 Supplementary Materials). The measurement campaign was nested within the Amsterdam Born Children and their Development (ABCD) study (7). We selected primary schools that were located in the Amsterdam area and that were attended by at least one child participating in the ABCD study. Within each school, two classrooms were selected based on the presence of children participating in the ABCD study. When more than two classrooms were available, the two classrooms furthest apart were selected for RF-EMF measurements. When there was only one child participating in the study in a school, only one classroom was measured.

Measurements in each classroom consisted of at least seven spot measurements of two min each, taking a reading once every four seconds. One measurement was taken in each corner of the room at 1.5 meters above the floor and 1.5 meters away from the walls. Three measurements were taken in the center of the room at 1.1, 1.5, and 1.7 meters above the floor, respectively. Up to three additional spot measurements were performed in irregular shaped rooms (87 classrooms). These additional spot measurements were taken at a height of 1.5 meters above the floor. This method is adapted from measurement recommendations by CENELEC (8) and used previously by Bürgi *et al* (9), who found that this method provides stable average exposure estimates. An adjustable wooden tripod was used to minimize interference of radio waves by metallic objects. Study assistants and any other persons present in the room were asked to turn off their mobile phones and to keep a distance of at least 1.5 meters during measurements to minimize interference with background exposure in the room. Measurements were taken in the afternoon directly after school hours, usually between 13:00 and 17:00 hours. The presence of DECT (digital enhanced cordless telecommunications) or WiFi base stations in or within 5 meters of the classroom was registered. An EME SPY 140 (SATIMO, EMF Measurement & Simulation Tools, France) exposure meter with the ability to measure 14 different frequency bands, ranging from FM to WiFi 5G was used. The detection limit for mobile phone and WiFi frequency bands is 6.64×10^{-2} μW m^{-2} while the detection limits for other bands are higher (i.e. less sensitive): TETRA (2.65×10^{-1} μW m^{-2}), TV3 (1.06 μW m^{-2}), and FM (6.63 μW m^{-2}). The expanded uncertainty was calculated following the ECC Recommendation (02)04 (10) and can be found in Table 2.1. It was calibrated before the measurement campaign. The SATIMO device registers measurements below the detection limit as the value of the detection limit. For the statistical analysis, the measurements below the respective detection limits (censored values) were imputed using the robust regression order statistics (ROS) method per spot measurement sample. In this method a log-normal distribution is fitted to the observed data and used to model the censored values. Modeled censored values are then combined with observed values (11). All statistical calculations were performed using R version 3.2.2 (12). To evaluate contributions of indoor or outdoor sources to total exposure, the 14 frequency bands were additionally grouped into six categories: 1) broadcast (FM, TV3, TV45), 2) TETRA, 3) mobile phone uplink (GSM900, GSM1800, UMTS), 4) mobile phone downlink (GSM900, GSM1800, UMTS), 5) DECT (i.e. cordless landline phones), and 6) WiFi (WiFi 2G, WiFi 5G, WiMAX). A second distinction was made between outdoor sources (broadcast, TETRA, mobile phone download) and indoor sources (mobile phone upload, DECT, WiFi).

Results

Selected primary schools were located throughout the city of Amsterdam. The 102 schools accounted for 48% of all primary schools in Amsterdam. Spot measurements were taken in 201 classrooms. In general, two classrooms were measured, with an additional classroom measured in the first two schools visited, and a single classroom measured in five schools which were attended by only a single

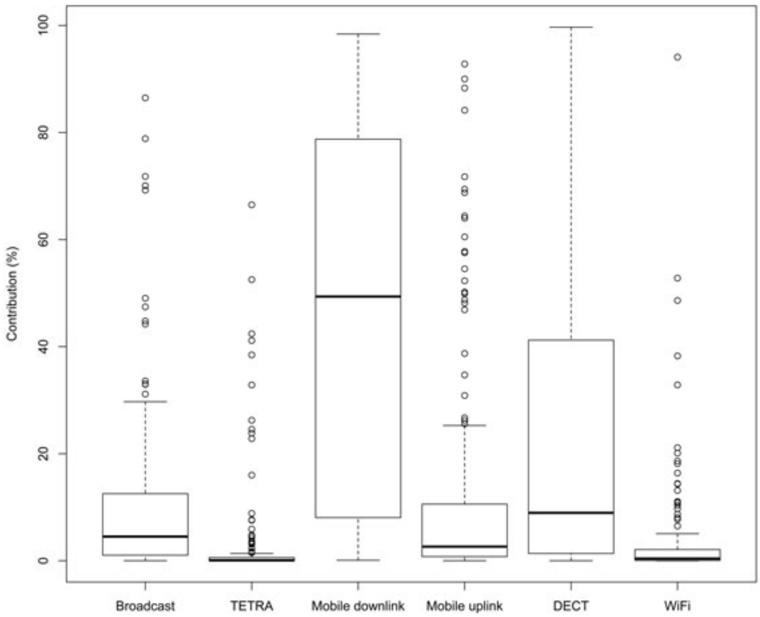

Figure 2.1: Relative contribution to average power density of all six categories (n=201).

ABCD study child. The average power density across all schools was 70.5 [Interquartile range 8.9-58.1] μW m^{-2} (0.16 V m^{-1}). Figure S2.2 (Supplementary Materials) shows the cumulative distribution function. For comparison, the ICNIRP guidelines (13), which are followed in the Netherlands, vary between 28 V m^{-1} and 61 V m^{-1} depending on the frequency. Table 2.1 summarizes the measurement results for each frequency band as well as their respective contributions to total average power density. WiFi 5GHz signals were not detected in any of the classrooms. Figure 2.1 shows the relative contribution of the six aforementioned categories to overall power density. All categories, with the exception of mobile phone downlink exposures, were strongly skewed to the right. The relative contribution varied strongly, in particular for mobile phone downlink signals (median 44.4% [Interquartile range 7.5-78.2]). TETRA and WiFi categories had small interquartile ranges, indicating low variability. In only a few classrooms they would contribute more than 50% to overall power density. Figure 2.2 shows the overall power densities for the six categories, stratified by the recorded absence or presence of WiFi routers, or DECT base stations. The contribution of broadcast signals remains similar over all four groups, while the other categories vary more strongly. The contribution of WiFi is higher in the groups with a recorded WiFi router. Conversely, DECT contribution is highest in the group where no DECT base station or WiFi router was registered. Overall, mobile phone downlink and DECT signals contributed most to total RF-EMF levels followed by broadcast and mobile uplink. WiFi contributed only a small fraction (4.5%) to total RF-EMF levels. The contribution to average power density from outdoor sources was somewhat higher (56.3%) compared to indoor sources (43.7%).

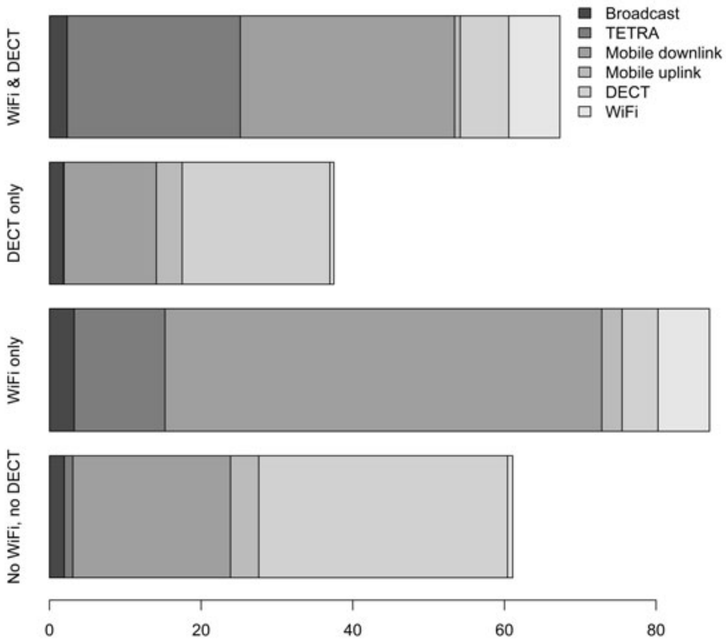

Figure 2.2: Relative contribution to average power density of all six categories (N=201).

Table 2.1: Frequency bands, expanded uncertainty, and results, average power density (μW m^{-2}) (n=201).

Band	Sources	Range (MHz)	Contribution[a]	Mean	SD	Expanded uncertainty (dB)
FM	Radio	88 – 108	5.47%	0.94	1.70	3.77
TV3	Digital audio	173 – 223	0.71%	0.12	0.36	2.60
TV45	Television	380 – 390	3.77%	1.56	8.39	3.04
TETRA	Terrestrial trunked radio	470 – 830	2.53%	2.11	13.10	2.89
GSM900 UL[b]	GSM mobile devices	880 – 915	7.77%	2.90	12.29	2.87
GSM900 DL[b]	GSM base stations	925 – 960	23.37%	12.35	30.88	2.90
GSM1800 UL[b]	GSM mobile devices	1710 – 1785	3.33%	1.06	3.05	2.75
GSM1800 DL[b]	GSM base stations	1805 – 1880	14.56%	8.39	26.81	2.73
DECT	Digital Enhanced Cordless Telephony	1880 – 1900	27.28%	35.18	162.18	1.85
UMTS UL	3G mobile devices	1920 – 1980	0.81%	0.10	0.44	1.80
UMTS DL	3G base stations	2110 – 2170	5.86%	3.43	8.69	2.22
WiFi 2G	Wireless networks	2400 – 2500	4.51%	2.40	11.90	2.72
WiFi 5G[c]	Wireless networks	3400 – 3800	-	-	-	5.93
WiMax	Wireless networks	5150 – 5850	0.02%	0.01	0.04	4.65

[a] Percentage of total RF-EMF levels detected.
[b] Uplink (UL) and downlink (DL) from point of view of mobile devices.
[c] No measurements above detection limit.

Discussion

RF-EMF exposure levels were determined for 201 classrooms in 102 primary schools in Amsterdam, resulting in an average power density of 70.5 μW m^{-2} (0.16 V m^{-1}). Main contributors to total RF-EMF levels were mobile phone downlink and DECT signals. Over half of detected signals (56.3%) originated from outdoor sources (i.e. mobile phone downlink, TETRA, broadcast). When looking at signals that originate from indoor sources (i.e. DECT, WiFi, mobile uplink), DECT was the main contributor followed by mobile phone uplink. Most variance was explained by differences between rooms, suggesting that measuring one single classroom per school is not enough to accurately represent RF-EMF levels for the entire school building. Individual spots inside a classroom were in near proximity of each other. Even so, the variance within/between spots accounted for 13.0%, indicating a location-driven variation. The presence of a WiFi router, as well as the floor the classroom appeared to have an effect on RF-EMF levels. The presence of a DECT base station, however, did not.
The main strength of our study was the large sample size, covering nearly half of all primary schools in Amsterdam, representing an urban setting. Limitations of our study include that measurements were done after school hours. As such, the influence of mobile communication devices used by children was not included. Mobile phones were turned off during measurements so they would not provide an additional indoor source. This means that the contribution of indoor sources has most likely been underestimated. Since the time of our measurement campaign, LTE networks and WiFi 5GHz have become more common, as such this exposure would likely be detected nowadays. Secondly, with 7-10 measurement spots the measurement time per classroom was limited to 14-20 min. This means that information on temporal variation is limited. The authors have previously repeated outdoor RF-EMF measurements over several months and found that exposure levels remained quite stable over time (14). Other studies in school environments carried out in Belgium and Greece by Verloock *et al.* (5) and Vermeeren *et al.* (6) have found RF-EMF levels of 0.40 V m^{-1} and 0.35 V m^{-1} respectively, roughly double the RF-EMF levels that were measured in this study. Possibly these differences could have been introduced by differences in measurement protocols, where Verloock *et al.* focused their selection on schools with WiFi availability and the presence of other indoor RF sources. Similarly, Vermeeren *et al.* performed measurements in rooms where highest exposure was expected (i.e. containing DECT base stations and/or WiFi access points). It was found that on average 43.4% of RF-EMF levels originated from indoor sources,

with DECT being the main contributor. When comparing average contributions to previously reported levels, both similarities and differences can be found. It was found that the main overall contributor to total exposure was mobile phone downlink, which is in line with results from Markakis and Samaras (3) and Vermeeren *et al*., 2013(6). Similarly, Frei *et al*. (15) found mobile phone downlink to be the main contributor during personal exposure measurements. The contribution of other bands differs, with DECT contribution in other publications ranging from 4% to 33% (3,6,15). While absolute levels were low, indoor sources may be of interest because they represent a source of exposure that can be influenced/changed.

Conclusion

Low RF-EMF levels were found in a large sample of primary schools in Amsterdam with mobile phone downlink (37.9%) and DECT (27.3%) signals being the major contributors. While our analysis indicates that presence of a WiFi router has a small influence on RF-EMF levels, absolute levels were low with WiFi signals in classrooms contributing just 4.5% of total RF-EMF levels. While the absolute RF-EMF levels are low, some influence can still be exerted by controlling indoor sources.

Acknowledgements

We thank the ABCD assistants Nikki Emmerik, Sjoukje Mos, Marcelle van der Putten, Maaike Schelling, Ilona Steenkamer and Hilde Stegeman for performing the measurements in the schools.

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2

Supplementary Materials

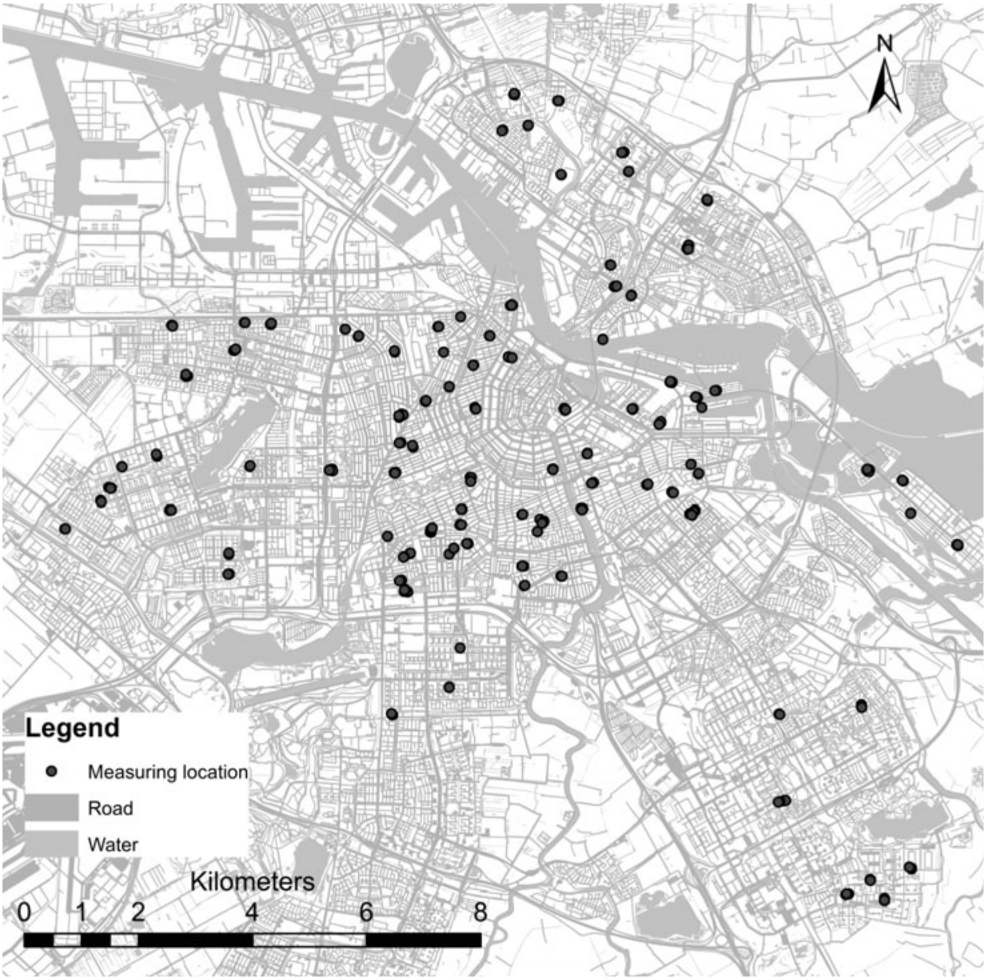

Figure S2.1: Measurement locations in Amsterdam, the Netherlands.

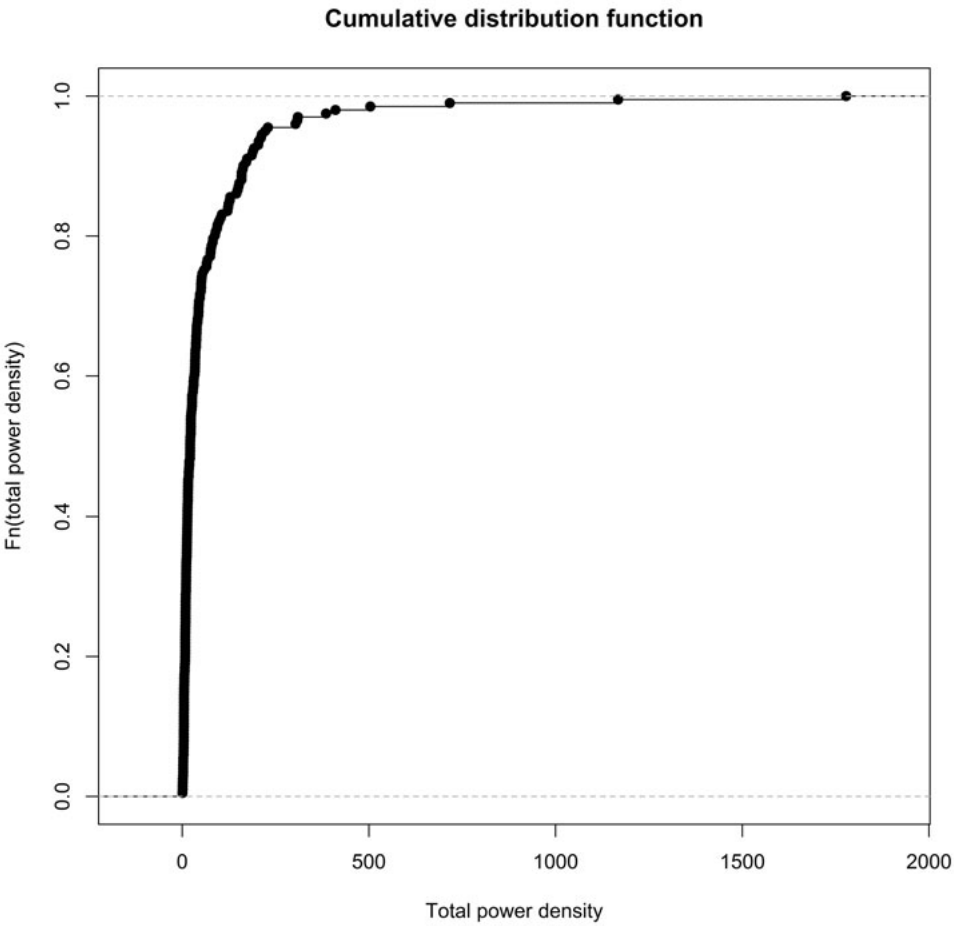

Figure S2.2: Cumulative distribution function of total RF-EMF levels.

CHAPTER 3

Validation of mobile phone use recall in the multinational MOBI-Kids study

Luuk van Wel, Anke Huss, Hans Kromhout, Franco Momoli, Daniel Krewski, Chelsea E. Langer, Gemma Castaño-Vinyals, Michael Kundi, Milena Maule, Lucia Miligi, Siegal Sadetzki, Alex Albert, Juan Alguacil, Nuria Aragones, Francesc Badia, Revital Bruchim, Geertje Goedhart, Patricia de Llobet, Kosuke Kiyohara, Noriko Kojimahara, Brigitte Lacour, Maria Morales-Suarez-Varela, Katja Radon, Thomas Remen, Tobias Weinmann, Martine Vrijheid, Elisabeth Cardis, Roel Vermeulen.

On behalf of the MOBI-Kids consortium

Manuscript being prepared for submission

Abstract

Objective To identify patterns in recall and differences across case-control status in studies of mobile phone use and cancer.

Methods A retrospective validation study within the multinational MOBI-Kids case-control study compared self-reported mobile phone use with network operator billing record data up to 3 months, up to 1 year, and up to 2 years before the interview date. Data were available for 702 subjects ranging from 10-24 years of age in 8 countries. Spearman rank correlations, Kappa coefficients and geometric mean ratios were used to compare self-reported versus operator recorded recall in cases and controls.

Results No apparent differences in recall of cases and controls were observed. However, both systematic and random non-differential recall errors were seen, with underreporting of the number of calls and overreporting of average call duration. Country, years since start of using a mobile phone, age at time of interview, and sex did not appear to influence recall accuracy for either call number or call duration. A trend in recall error was seen with level of self-reported mobile phone use, with underestimation of use at lower levels and overestimation of use at higher levels for both number and duration of calls.

Conclusion Although both systematic and random errors in self-reported mobile phone among participants in the MOBI-KIDS study were observed, there was no evidence of differential recall error between cases and controls. Nonetheless, these sources of exposure measurement error warrant consideration in the on-going analysis of the MOBI-KIDS case-control study of the association between children's use of mobile phones and potential brain cancer risk.

Introduction

In 2011, radiofrequency (RF) fields were classified as possibly carcinogenic to humans (IARC classification 2B) by the International Agency for Research on Cancer (1). In 2015, the Scientific Committee on Emerging and Newly Identified Health Risks (SCENIHR) published their final opinion on potential health effects of exposure to electromagnetic fields, concluding that studies do not show an increased risk of brain tumors. For longer-term exposures, gaps in terms of objective exposure monitoring were noted (2). The classification was based on findings in adults, who were the main focus of studies involving RF field and health outcomes at the time. Concern regarding potential health effects of RF fields exposure in children and adolescents has been growing due to the rapid increase in mobile phone use in younger age groups, who have longer lifetime exposure, potentially increased sensitivity due to a developing neurological system, and higher specific absorption rate (SAR) in the most highly exposed parts of the brain compared to adults due to their thinner skull and ears (3). Both national and international research bodies have recommended RF exposure from mobile phones in children and adolescents as a high priority research area (4,5). The MOBI-Kids study was designed to address concerns about a possible association between the carcinogenic effect of mobile phone use among children and young adults and brain cancer risk (6). The MOBI-Kids study builds upon the methodology of the INTERPHONE study, a multinational collaboration which investigated associations between mobile phone use and multiple types of brain tumors in adults (7). Reliability and accuracy of risk estimation in studies on mobile phones depends on the quality of the exposure ascertainment, which is most often based on self-reported mobile phone use. It is therefore important to understand and characterize the ability of participants to validly and precisely recall their mobile phone use (MPU). Errors in a participants' MPU recall may be non-differential (i.e., the same for both cases and controls), leading to increased uncertainty and under- or overestimation of risk estimates. There can also be differential recall errors, where cases may recall mobile phone use patterns differently from controls for various reasons, possibly due to either having more trouble remembering details or focusing more on past exposure as potential cause for their illness. The effect of differential error on risk estimates are often difficult to predict (8). As such, reliability of the overall MOBI-Kids findings on the association between mobile phone use and brain cancer risk will depend on the ability to account for inaccuracies and imprecision in self-reported MPU.
The MOBI-Kids study included two MPU validation efforts. The first was the

3

prospective Mobi-Expo validation study, which compared MPU information gathered using software modified smartphones to self-reported MPU at several time points, and found that young people can recall MPU moderately well, with recall depending on the amount of phone use (9). As this study only included healthy subjects, it could not provide information on potential differential recall errors between brain tumor cases and controls. The second validation study, a retrospective effort comparing self-reported MPU of consenting subjects to their phone records obtained from mobile network operators, is described here. The aim of this study was to compare the accuracy of MPU reporting of cases having a primary brain tumor with that of controls who underwent an appendectomy, with recall for three time periods: up to 3 months, 1 year, and 2 years preceding the MPU interview, providing insight into patterns of non-differential or differential recall error. The effects of various demographic variables and of the amount of phone usage on MPU recall are also investigated.

Methods

The multinational MOBI-Kids study, in which this retrospective validation study is embedded, recruited participants from May 2010 to March 2016 within 14 participating countries. All males and females from 10 to 24 years of age within the study regions with a confirmed diagnosis of an eligible first primary brain tumor during the study period were included in the target population (6). Both benign and malignant tumors originating in those parts of the brain likely to experience the highest RF-EMF exposure from mobile phones were included, with midline tumors excluded. Cases not speaking the study language within their country/region or having a known genetic syndrome related to brain tumors were excluded (6). Cases were identified from appropriate hospital departments. For each case, two hospital-based controls (receiving an appendectomy for suspected appendicitis) were selected, matched on age, sex, date of surgery/interview, and geographic area of residence. Included subjects were interviewed to ascertain their lifetime self-reported MPU and were asked to provide informed consent to obtain MPU information from their mobile phone network operator. Case interviews took place within 12 months of their date of diagnosis; control interviews were scheduled within 12 months of the matched case's interview. The study design was approved by the Institutional Review Boards in each country and all participants provided their informed consent. Further details of the MOBI-Kids study recruitment procedures can be found elsewhere (6).

Validation study population

A total of 844 subjects (30% of total subjects in MOBI-Kids) consented to obtaining their billing record data for validation of self-reported mobile phone utilization. Billing record data was available for 806 subjects, of which 781 also had self-reported MPU data. As an overlap between available operator data and interview data of at least one of 3 months preceding the interview was required, subjects who did not have operator data available in any of the 3 months preceding the interview data were excluded. This resulted in a total of 702 subjects remaining for inclusion in this validation study (24.8% of all MOBI-Kids subjects) (Supplementary materials, Figure S3.1). In addition to the main analysis with subjects who had data in the 3 months preceding the interview, subsets of subjects with operator data available for the entire year preceding the interview (N=357) and 2 years of operator data available preceding the interview (N=104) were investigated.

Self-reported mobile phone use

Subjects were administered a detailed questionnaire by trained interviewers. This included questions regarding the type of mobile phone, the network operator, and their MPU including both voice and data. Subjects were asked about the number and duration of calls for multiple time periods: at the beginning of using a mobile phone, current use (i.e., last 3 months preceding the interview), and changes in between. Subjects (or their legal guardian, as appropriate) were asked whether they agreed to take part in the operator data validation study. Those who agreed signed an informed consent form authorizing the operators to provide their phone use data for the purpose of the study and listed the time periods in which they used different phone numbers and network operators. In addition, interviewers reported how they perceived the responsiveness of subjects during the interview, with a score ranging from “not at all (uninterested, reticent)”, “fairly co-operative and responsive”, to “very co-operative, responsive and interested”.

Recorded mobile phone use (operator data)

Study centres contacted mobile phone operators in participating countries, informed them of the study and asked for their collaboration. The data that could be obtained from records of consenting study participants and the length of time covered by records varied by operator and country for legal and logistic reasons. Phone calls in operator records were recorded in both number and duration of calls (in minutes) per month. This information was either separated into incoming calls and outgoing calls or presented as a sum of both incoming and outgoing calls, depending on the network operator involved.

Statistical analysis

The comparison of self-reported MPU and recorded MPU was conducted separately for the number and duration (in minutes) of calls in the 3 months preceding the date of interview. In addition, a subset of subjects who had data available for 1 year, and a subset for 2 years preceding the date of interview were assessed. Separate incoming and outgoing calls were summed to represent all calls per month of available data. For 67 subjects (9.6%), at least one month of operator data had partial missing information on either incoming or outgoing calls (e.g., only incoming number of calls was recorded, with missing information on the outgoing number of calls that month). For these months, missing information was multiply imputed (100 times), drawing values from the expected value with corresponding variance, based on a mixed model that modelled the number of calls or duration of calls per month as the dependent variable and modelled type of call (i.e., incoming or outgoing), age and gender (both as interaction term with type of call) as independent variables. The model included random nested intercepts for individuals and country and used a heterogeneous compound symmetry structure for covariance to take into account the similarity in measures within the same person over time. Months where information on incoming and outgoing calls was entirely missing for number of and/or duration of calls, were excluded. For some subjects information on number and duration of calls for one (N=122; 17.5%) or two (N=30; 4.3%) months of operator data in the 3 months preceding the interview was missing. In these cases, the average of the available month(s) in the 3-month time window was taken as the MPU in the missing month(s). from the dataset. Agreement between self-reported and operator recorded MPU was evaluated using the Spearman rank-order correlation coefficient on the natural scale, and by a kappa-statistic on categorized variables (i.e., quintiles of MPU in control group).

As both the Spearman and kappa-statistic do not provide information on the amount of over- or underreporting the geometric mean ratio (GMR) of self-reported MPU and recorded MPU values was used for this purpose. The GMR was calculated by taking the exponent of the mean of the logarithms of all self-reported MPU to recorded MPU ratios. A corresponding standard error of the mean was calculated by non-parametric bootstrapping, which in turn was used to calculate a 95% confidence interval for the GMR. The ratio represents the level of underestimation (GMR <1) or overestimation (GMR >1) of MPU, while the variance provides information on the random error in recall. Bland-Altman plots showing the ratio of self-reported to recorded MPU (log-transformed) against mean self-reported and recorded MPU (log-transformed) were used to further illustrate the relationship of recalled to recorded MPU, with the limits of agreement providing a graphical representation of the random error.

Two sensitivity analyses were performed by 1) excluding all participants who scored 1 or 2 (not at all interested; fairly co-operative and responsive) on the interview responsiveness score, and 2) excluding all participants with any missing data (either on questionnaire or operator data). All analyses were performed using SAS software version 13.2 (SAS Institute Inc) and R version 3.4.1 (R Foundation for Statistical Computing, Vienna, Austria).

Results

A total of 702 subjects from eight different countries (Canada, France, Germany, Greece, Israel, Italy, Korea, and Spain) had data on both self-reported and recorded MPU in the 3 months preceding the interview date (Table 3.1). There were 250 (35.6%) cases and 452 (64.4%) controls, reflecting the matching of two controls to each case in the MOBI-Kids study population. 45.4% of the subjects were female, and the mean age was 17.5 years old (standard deviation 4.0). These numbers are similar to the main MOBI-Kids study population (Supplementary materials, Table S3.1).

Mobile phone use

The absolute number of calls and duration of calls (in minutes) in the 3 months preceding the interview are shown in Table 3.1. For both self-reported and recorded data, subjects from Israel had considerably higher MPU compared to subjects from other countries (Supplementary materials, Figures S3.2 and S3.3). Minimum and maximum mobile phone use varied considerably for both cases and controls in all countries.

Correlation and agreement of self-reported and recorded MPU

The Spearman rank correlation coefficients comparing self-reported and recorded MPU in the most recent 3 months were 0.57 for call number and 0.59 for call

Table 3.1: Self-reported and recorded number and duration of calls, shown by case-control status per country.

		Number of calls (number in 3 months)		Duration of calls (minutes in 3 months)	
		Self-reported	Recorded	Self-reported	Recorded
Country	N	Median (min-max)	Median (min-max)	Median (min-max)	Median (min-max)
Cases	*250*	*196 (0 – 4566)*	*260 (0 – 7128)*	*861 (0 – 37474)*	*388 (0 – 12269)*
Canada	3	183 (65 - 502)	482 (57 - 924)	360 (196 - 4109)	1131 (73 - 5559)
France	59	130 (13 - 2055)	258 (18 - 1617)	489 (13 - 9723)	350 (17 - 5774)
Germany	21	91 (0 - 913)	137 (22 - 639)	457 (0 - 5479)	175 (19 - 2731)
Greece	1	137 (137 - 137)	276 (276 - 276)	411 (411 - 411)	273 (273 - 273)
Israel	28	502 (28 - 4566)	913 (73 - 7128)	1517 (99 - 16436)	1396 (3 - 12269)
Italy	99	228 (3 - 2739)	221 (0 - 2411)	913 (21 - 16436)	355 (0 - 8634)
Korea	4	685 (320 - 1598)	654 (99 - 1308)	1027 (548 - 2283)	682 (79 - 1002)
Spain	35	137 (9 - 2055)	213 (11 - 943)	326 (13 - 37474)	322 (15 - 7998)
Controls	*452*	*224 (0 – 6392)*	*308 (0 – 10496)*	*666 (0 – 32240)*	*424 (0 – 28645)*
Canada	2	176 (33 - 320)	82 (24 - 141)	502 (91 - 913)	307 (26 - 588)
France	97	224 (12 - 6392)	356 (23 - 6570)	679 (20 - 21862)	428 (18 - 8141)
Germany	19	91 (26 - 2496)	204 (6 - 809)	1175 (30 - 10958)	217 (0 - 2068)
Greece	1	75 (75 - 75)	106 (106 - 106)	75 (75 - 75)	197 (197 - 197)
Israel	46	639 (26 - 3652)	858 (0 - 10496)	1373 (26 - 32240)	1128 (0 - 13383)
Italy	211	228 (9 - 2739)	255 (0 - 2772)	639 (13 - 18784)	349 (0 - 28645)
Korea	8	616 (120 - 2739)	370 (81 - 878)	845 (135 - 4109)	792 (162 - 2634)
Spain	68	91 (0 - 3652)	334 (6 - 1608)	228 (0 - 24654)	367 (3 - 3756)

duration. Correlations remained similar when stratified by case-control status. For cases, the correlation coefficients were 0.59 and 0.63 for number and duration of calls, respectively; for controls they were 0.56 and 0.57, respectively. When increasing the time period, cases showed a lower correlation for call number over 2 years compared to controls, although little difference in the correlation for the duration of calls was observed (Table 3.2).

When MPU was categorized using cut-off values based on quintiles from the combined recorded and reported number of calls of the control group, kappa values at 3 months were similar for cases and controls (Table 3.3). When increasing the time period for the number of calls, the weighted (equal spacing) kappa statistic for controls was similar to the cases at the 1-year time period (0.46 versus 0.45) but higher at the 2-year time period (0.50 versus 0.31). Similar results were seen for the duration of calls: at 1 year 0.48 versus 0.44, and at 2 years 0.46 versus 0.36 (not shown).

Table 3.2: Spearman rank correlation coefficients for self-reported versus recorded MPU.

	Number of calls						Duration of calls					
	Overall		Cases		Controls		Overall		Cases		Controls	
Time period	N	p	N	p	N	p	N	p	N	p	N	p
Up to 3 months	702	0.57	250	0.59	452	0.56	702	0.59	250	0.63	452	0.57
Up to 1 year	357	0.64	131	0.67	226	0.62	357	0.65	131	0.69	226	0.64
Up to 2 years	104	0.58	41	0.42	63	0.66	104	0.64	41	0.63	63	0.66

Table 3.3: Categorical comparison (quintiles of control group) of self-reported and recorded number and duration of calls in the most recent 3 months. Numbers shown are number of subjects.

Recorded number of calls (number in 3 months)	Self-reported number of calls (number in 3 months)				
	0-80.3	80.4-182.9	193-355.9	356-616.9	617+
Cases					
0-80.3	**24**	9	9	1	1
80.4-182.9	22	**6**	16	6	3
193-355.9	14	17	**11**	5	5
356-616.9	2	8	13	**6**	9
617+	1	4	14	17	**27**
Kappa-statistic	*0.37*				
Absolute agreement	*0.30*				
Controls					
0-95.1	**42**	12	4	5	2
95.2-212.9	36	**24**	14	6	5
213-370.9	17	21	**32**	20	9
371-635.9	12	18	28	**29**	19
636+	9	9	15	15	**49**
Kappa-statistic	*0.41*				
Absolute agreement	*0.39*				
Recorded duration of calls (minutes in 3 months)	Self-reoprted duration of calls (minutes in 3 months)				
	0-131.9	132-353.9	354-749.9	750-1929.9	1930+
Cases					
0-131.9	**26**	16	8	6	5
132-353.9	16	**11**	11	17	5
354-749.9	2	6	**11**	17	14
750-1929.9	1	2	5	**18**	22
1930+	1	1	4	6	**19**
Kappa-statistic	*0.38*				
Absolute agreement	*0.34*				
Controls					
0-131.9	**49**	17	7	13	5
132-353.9	25	**30**	20	25	10
354-749.9	9	12	**27**	34	22
750-1929.9	3	9	16	**17**	37
1930+	3	4	6	10	**42**
Kappa-statistic	*0.39*				
Absolute agreement	*0.37*				

3

Recall error

There were no major differences in GMRs between cases and controls either in the overall analysis or in the stratified analysis for the duration of calls (Table 3.5), suggesting an absence of differential recall error between cases and controls. For call number, there was a significant difference in recall between cases and controls in the middle quintile (40th-60th percentile) of self-reported MPU, but not in the other categories of self-reported MPU (Table 3.4).

The overall GMRs of self-reported versus recorded MPU in the most recent 3 months were 1.59 for call duration and 0.69 for call number, indicating systematic errors in the form of overreporting of call duration of calls and underreporting of the number of calls. Looking at recall over time for subjects with 2 years of data available, there appears to be a lower level of overreporting of duration of calls for both cases (initial GMR 1.62, 1.44 at 1 year) and controls (initial GMR 1.37, 1.08 at 1 year) between recent recall and 1 year. There is however little difference between the 1 and 2 year time points for either cases or controls (1.44 vs 1.41 and 1.08 vs 1.07, respectively, for call duration) (Table 3.5). Although this same initial decrease can be seen in controls for call number, it is less clear for cases (Table 3.4).

Further analyses stratifying by country, reported years since start of mobile phone use, sex, and age at time of the interview showed differences in GMRs in all groups, but little statistical evidence of heterogeneity (while some statistically significant differences were noted, the magnitude of such differences was small). Comparison of recall of both duration and number of calls by age within cases revealed some evidence of heterogeneity, with the 15-19 year old age group having a GMR of 2.25 for call duration compared to 1.11 and 1.62 in the other age groups (Table 3.5). Differences were less pronounced for call number (0.87 for 15-19 year old versus 0.59 and 0.67 in the other age groups) (Table 3.4). When categorizing subjects by self-reported levels of MPU, a trend was seen with underreporting of MPU in the lower categories and over reporting of MPU in the higher categories. This was seen for both call duration and call number in both cases and controls. A graphical illustration of these results is given in Figure 3.1 (duration of calls) and Figure 3.2 (number of calls). In addition to systematic error, the limits of agreement shown in these figures indicate a substantial amount of random error. As underreporting in the lowest category indicates that the actual value lies closer to the overall mean (i.e., the MPU would be higher than reported), and over reporting in the highest category indicates a lower actual MPU than reported, the actual contrast between lowest and highest groups may be smaller than these results suggest.

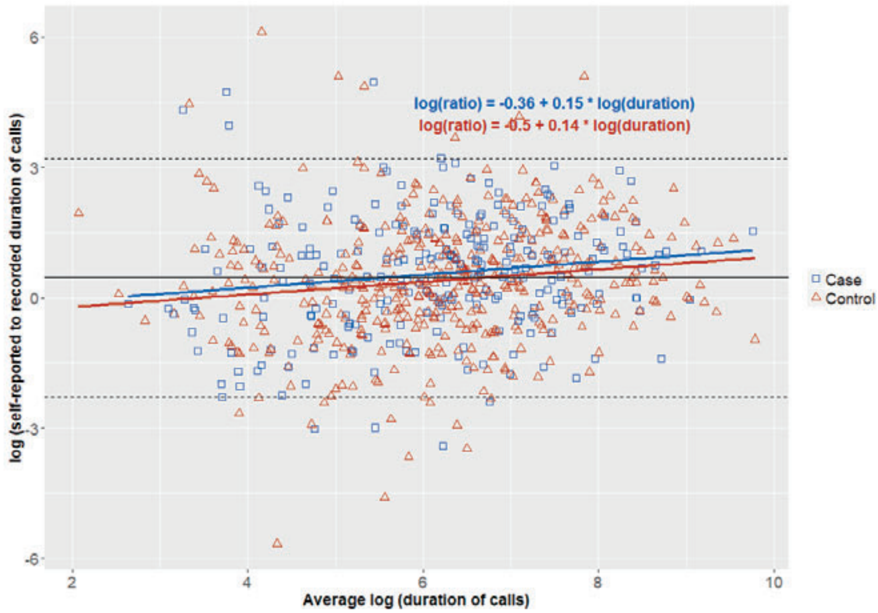

Figure 3.1: Ratio of self-reported to recorded duration of calls against mean phone use (log-transformed data) with dashed lines indicating the 95% limits of agreement and the red (control) and blue (case) lines indicating the corresponding regression line. Average is the average of self-reported and recorded duration of calls. P for interaction term, 0.78.

Sensitivity analysis

Two sensitivity analyses were performed. No major differences were found when only looking at subjects who were very co-operative, responsive and interested during the interview (N=527). The overall GMRs for call duration (1.61 versus 1.59 in main analysis) and call number (0.71 versus 0.69) were similar. Similarly, we observed no material differences in results when restricting to subjects without missing data (N=497), with GMRs of 1.56 and 0.67 for call duration and call number, respectively.

Table 3.4: Ratio of self-reported versus recorded mobile phone use in number of calls, shown by case-control status.

Number of calls	Cases			Controls			
	N	GMR[a]	95%-CI	N	GMR[a]	95%-CI	P for difference[b]
Overall (at 3 months)	*250*	*0.72*	*0.63, 0.83*	*452*	*0.69*	*0.61, 0.76*	*0.48*
Subset: 1 year of data							
Up to 3 months	131	0.80	0.66, 0.98	226	0.69	0.60, 0.79	0.20
Up to 1 year	131	0.69	0.58, 0.81	226	0.65	0.57, 0.74	0.52
Subset: 2 years of data							
Up to 3 months	41	0.74	0.55, 1.01	63	0.68	0.53, 0.87	0.66
Up to 1 year	41	0.65	0.49, 0.86	63	0.59	0.47, 0.76	0.64
Up to 2 years	41	0.68	0.50, 0.92	63	0.59	0.46, 0.76	0.50
Subset: 2 years of data							
Months 1-3	41	0.74	0.55, 1.00	63	0.68	0.46, 0.76	0.83
Months 4-12	41	0.64	0.47, 0.87	63	0.59	0.46, 0.76	0.73
Months 13-24	41	0.73	0.51, 1.03	63	0.58	0.45, 0.76	0.30
By country							
Canada	3	0.62	0.37, 1.04	2	1.76	1.23, 2.50	0.06
France	59	0.53	0.40, 0.69	97	0.56	0.45, 0.69	0.96
Germany	21	0.58	0.35, 0.95	19	0.88	0.53, 1.47	0.24
Greece	1	0.50	0.50, 0.50	1	0.71	0.71, 0.71	-
Israel	28	0.62	0.46, 0.83	46	0.76	0.53, 1.09	0.39
Italy	99	1.02	0.80, 1.30	211	0.83	0.73, 0.95	0.15
Korea	4	2.48	0.57, 10.72	8	1.48	0.48, 4.55	0.59
Spain	35	0.54	0.38, 0.76	68	0.39	0.27, 0.57	0.23
P for heterogeneity	*0.23*			*0.23*			
By reported years since start of mobile phone use							
1-2.9	35	0.42	0.27, 0.67	72	0.58	0.40, 0.83	0.31
3-4.9	43	0.69	0.50, 0.95	90	0.60	0.49, 0.72	0.52
5-6.9	51	1.04	0.77, 1.41	86	0.72	0.56, 0.93	0.07
7-8.9	50	0.77	0.56, 1.08	68	0.81	0.63, 1.06	0.91
9+	65	0.73	0.57, 0.93	119	0.76	0.63, 0.92	0.87
P for heterogeneity	*0.38*			*0.29*			
By sex							
Male	138	0.71	0.58, 0.87	246	0.65	0.56, 0.75	0.38
Female	112	0.73	0.60, 0.91	206	0.73	0.62, 0.86	0.94
P for heterogeneity	*0.62*			*0.18*			
By age							
10-14 years	53	0.59	0.41, 0.85	114	0.64	0.50, 0.82	0.73
15-19 years	98	0.87	0.67, 1.12	180	0.69	0.58, 0.81	0.12
20-24 years	99	0.67	0.56, 0.80	158	0.72	0.60, 0.85	0.68
P for heterogeneity	*0.04*			*0.32*			
By self-reported level of mobile phone use							
$<$20th percentile	42	0.22	0.16, 0.30	81	0.26	0.19, 0.34	0.44
20th-40th percentile	48	0.47	0.38, 0.59	86	0.50	0.39, 0.63	0.76
40th-60th percentile	56	0.93	0.69, 1.25	90	0.64	0.54, 0.75	0.02
60th-80th percentile	51	0.94	0.74, 1.19	99	1.01	0.86, 1.19	0.66
$>$80th percentile	53	1.59	1.23, 2.04	96	1.51	1.22, 1.85	0.75
P for heterogeneity	*0.004*			*0.02*			

[a] Geometric mean of ratio self-reported versus recorded mobile phone use.
[b] Log ratios were compared using a t-test with unequal variances.

Table 3.5: Ratio of self-reported versus recorded mobile phone use in duration of calls (in minutes), shown by case-control status.

Duration of calls	Cases			Controls			
	N	GMR[a]	95%-CI	N	GMR[a]	95%-CI	P for difference[b]
Overall (at 3 months)	*250*	*1.70*	*1.43, 2.03*	*452*	*1.53*	*1.34, 1.75*	*0.26*
Subset: 1 year of data							
Up to 3 months	131	1.92	1.51, 2.45	226	1.52	1.28, 1.81	0.10
Up to 1 year	131	1.63	1.33, 2.00	226	1.37	1.16, 1.60	0.14
Subset: 2 years of data							
Up to 3 months	41	1.90	1.23, 2.96	63	1.41	1.01, 1.98	0.29
Up to 1 year	41	1.47	1.01, 2.13	63	1.08	0.80, 1.47	0.22
Up to 2 years	41	1.44	0.99, 2.09	63	1.07	0.78, 1.46	0.25
Subset: 2 years of data							
Months 1-3	41	1.90	1.22, 2.96	63	1.40	1.00, 1.97	0.62
Months 4-12	41	1.50	1.02, 2.19	63	1.09	0.80, 1.49	0.32
Months 13-24	41	1.52	0.98, 2.35	63	1.12	0.79, 1.58	0.35
By country							
Canada	3	0.86	0.32, 2.33	2	2.36	1.32, 4.21	0.19
France	59	1.10	0.82, 1.49	97	1.52	1.21, 1.90	0.21
Germany	21	2.60	1.21, 5.55	19	3.35	1.55, 7.20	0.66
Greece	1	1.51	1.51, 1.51	1	0.38	0.38, 0.38	-
Israel	28	1.52	0.90, 2.57	46	1.55	1.06, 2.27	0.96
Italy	99	2.36	1.78, 3.13	211	1.70	1.43, 2.01	0.06
Korea	4	2.62	0.99, 6.89	8	1.08	0.39, 3.01	0.24
Spain	35	1.27	0.81, 1.98	68	0.96	0.60, 1.53	0.40
P for heterogeneity	*0.21*			*0.46*			
By reported years since start of mobile phone use							
1-2.9	35	0.96	0.56, 1.63	72	1.19	0.79, 1.78	0.58
3-4.9	43	2.12	1.37, 3.30	90	1.70	1.29, 2.24	0.40
5-6.9	51	2.01	1.38, 2.93	86	1.94	1.43, 2.64	0.82
7-8.9	50	1.95	1.33, 2.86	68	1.71	1.29, 2.26	0.57
9+	65	1.72	1.27, 2.33	119	1.39	1.09, 1.76	0.21
P for heterogeneity	*0.29*			*0.86*			
By sex							
Male	138	1.73	1.36, 2.19	246	1.40	1.18, 1.67	0.17
Female	112	1.68	1.29, 2.18	206	1.71	1.40, 2.08	0.92
P for heterogeneity	*0.30*			*0.16*			
By age							
10-14 years	53	1.11	0.73, 1.68	114	1.39	1.03, 1.88	0.35
15-19 years	98	2.25	1.66, 3.04	180	1.78	1.45, 2.19	0.13
20-24 years	99	1.62	1.29, 2.04	158	1.39	1.15, 1.68	0.18
P for heterogeneity	*0.04*			*0.79*			
By self-reported level of mobile phone use							
$<$20th percentile	43	0.37	0.27, 0.52	74	0.46	0.33, 0.64	0.37
20th-40th percentile	46	1.39	0.92, 2.11	99	0.95	0.75, 1.21	0.12
40th-60th percentile	38	1.83	1.24, 2.69	85	1.26	1.03, 1.55	0.05
60th-80th percentile	73	2.32	1.83, 2.95	95	2.82	2.18, 3.63	0.32
$>$80th percentile	50	4.36	3.18, 5.97	99	3.96	3.18, 4.93	0.64
P for heterogeneity	*0.06*			*0.02*			

[a] Geometric mean of ratio self-reported versus recorded mobile phone use.
[b] Log ratios were compared using a t-test with unequal variances.

3

Figure 3.2: Ratio of self-reported to recorded number of calls against mean phone use (log-transformed data) with dashed lines indicating the 95% limits of agreement and the red (control) and blue (case) lines indicating the corresponding regression line. Average log is the average of self-reported and recorded number of calls. P for interaction term, 0.56.

Discussion

In this validation study, we evaluated potential differential and non-differential recall error in MPU between cases with a first primary brain tumor and controls. Self-reported MPU obtained from interviews was compared with network operator records in the 3 months, 1 year, and 2 years preceding the interview date. We did not find evidence of differential recall error between cases and controls based on Spearman rank correlations, kappa-statistics, or geometric mean ratios. Non-differential recall errors, both systematic and random, were observed with a systematic underestimation of the number of calls and an overestimation of the call duration. A trend was observed between varying levels of self-reported mobile phone use, with underestimation at lower levels and overestimation at higher levels for both number and duration of calls.

Strengths and weaknesses

This is one of the few validation studies thus far comparing differences in recall between brain tumor cases and controls amongst children and adolescents, using both detailed self-reported data and objective network operator records. A major strength is the inclusion of a large number of adolescents and children from various countries both within and outside Europe.
Compared to the previous Mobi-Expo validation study using software modified phones to record MPU for a month (9), we obtained information on brain tumor cases as opposed to healthy volunteers. Given Mobi-Expo's prospective approach, subjects were aware of their inclusion in the study and knew they would be asked about their phone use, possibly influencing their MPU and/or responses, while this is not the case in the current retrospective approach. A drawback of using operator data is the fact that these data are often incomplete and not always available for the desired etiological period, particularly if this period is in the past, as is the case in our study. Additionally, it may not always be clear from billing records who the actual user of the phone was when making calls. While not all subjects from the main MOBI-Kids study provided informed consent to obtain their network operator data and not all operators provided data, we still managed to include a large proportion of subjects (24.8%) in this validation study. The proportion of subjects where longer-term data was available (1 and 2 year time periods) was smaller, with no subjects from some of the participating countries. The gender distribution in the validation study was the same as in the main MOBI-Kids study and the mean age differed by just one year (17.5 years versus 16.6 in the main study).

Case-control differences

Our data do not provide evidence of differential recall error between cases and controls. This is in line with findings from the INTERPHONE study, where recall error amongst adult cases and controls was investigated (10). Within INTERPHONE, no differences between cases and controls were found in regards to country, reported years of mobile phone use, sex, or age at time of interview. The CEFALO validation study also looked at differences between cases and controls in children and adolescents (11). While they found borderline significant evidence for more pronounced overestimation in controls compared to cases, this finding was not reproduced here. A potential explanation could be the larger number of subjects we included (135 in the CEFALO study versus 702 in our study) and the shorter time period between diagnosis and time of interview, which was 844 (for cases) or 886 (for controls) days for the CEFALO subjects, and within 365 days for our study.

Sensitivity analyses

The effect of responsiveness of subjects during the self-reported MPU interview, and the use of imputed data were investigated in sensitivity analyses. No major differences were noted, neither non-differential or differential, suggesting that these factors had little effect on our results. For interview quality, only 15 participants were judged to be poor responders (category "not at all responsive") while the other 160 subjects excluded in the sensitivity analysis were considered "fairly responsive", limiting the ability to draw informative conclusions from this.

Over- and underestimation

The overestimation of the duration of calls that we found is in line with previous validation studies among young people, although the degree of over-estimation differed (12,13). The comparison is less consistent for call number, where overestimation was found in the CEFALO (12) and SCAMP (13) studies. In Mobi-Expo the same direction of systematic error was found as in the current study, although the level was stronger in the current study (number of calls: GMR 0.52 versus 0.69, duration of calls: GMR 1.32 versus 1.59). The INTERPHONE validation study, performed among adults rather than adolescents and children, showed results in line with our current findings (overall GMR INTERPHONE 0.81 for number and 1.39 for duration of calls) (10). The INTERPHONE study found significantly differing ratios between countries. In the present study we did see some differences in GMRs among the eight participating countries, but the differences did not achieve statistical significance. In contrast, the Mobi-Expo validation study did find significant differences among countries (9). We observed differences in recall among age groups, with the 15-19-year-old group demonstrating the largest degree of overestimation for call duration in both cases and controls, and for call number in cases. These differences in recall of call duration and call number were statistically significant only in cases. The CEFALO validation study used two age groups (10-14 versus 15-19 years old) and found greater overestimation in the 15-19 year group for both call number and duration (12), while Kiyohara et al. (14), using the same age groups as our study, found that the youngest age group (10-14) had the highest overestimation. We did find some heterogeneity, but taken into account the differing results in previous studies we believe that the MOBI-Kids study should consider a difference in reporting by age group.

Conclusion

We compared self-reported MPU with operator data at 3 months, 1 year, and 2 years preceding the interview date. No indication of differential recall error between cases and controls was found. Both non-differential systematic and random errors were observed, with number of calls being underreported and duration of calls being over reported on average in both cases and controls. The non-differential random errors observed may bias risk estimates towards their null values and decrease study power. The present results will provide a basis for understanding and characterizing recall errors when evaluating the MOBI-Kids case-control study results.

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Declarations of interest

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Supplementary Materials

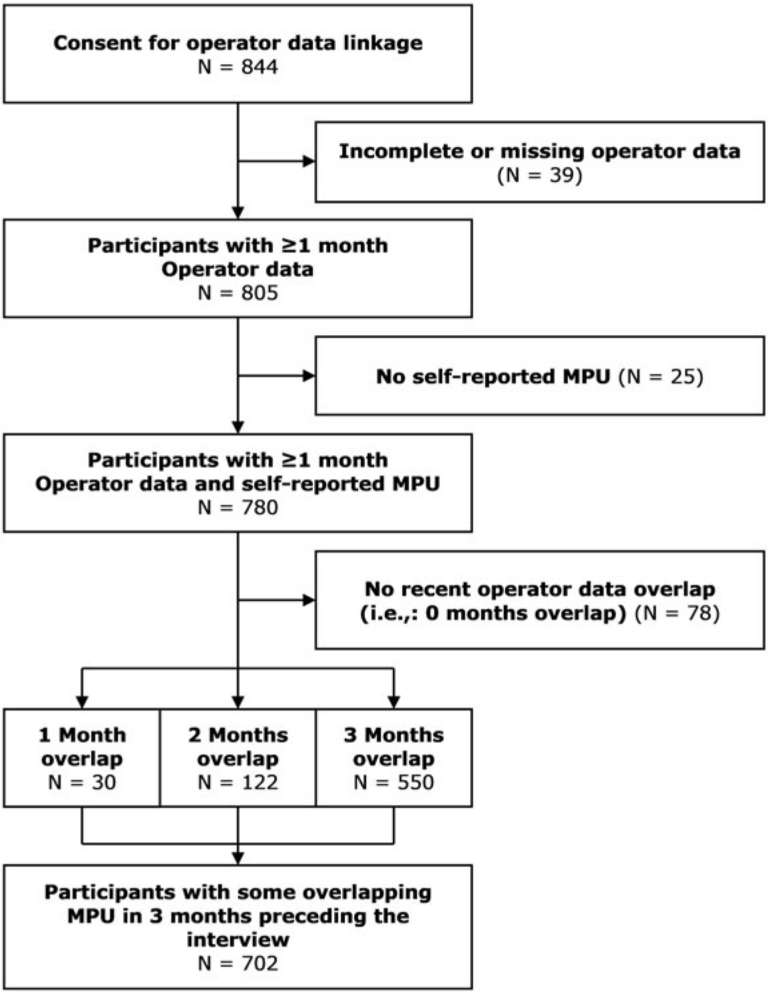

Figure S3.1: Participant flowchart (MPU is Mobile Phone Use).

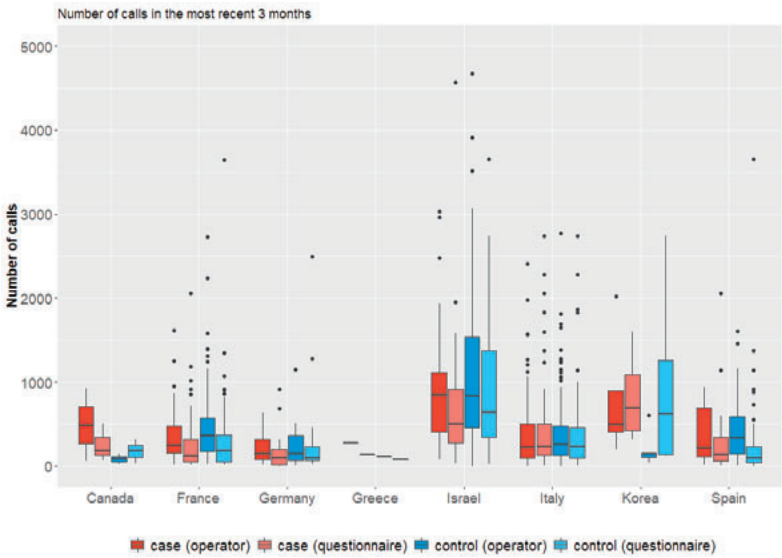

Figure S3.2: Distribution of the number of calls in the most recent 3 months given by case-control status in each of the countries.

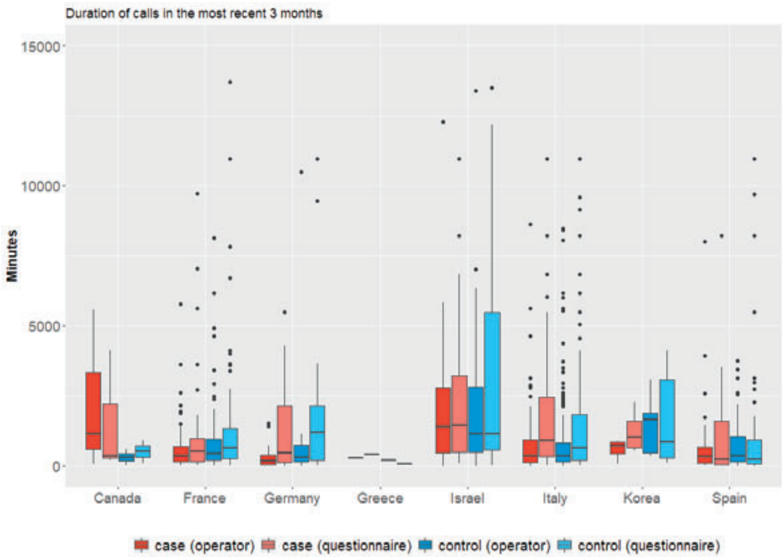

Figure S3.3: Distribution of the duration of calls (in minutes) in the most recent 3 months given by case-control status in each of the countries.

3

Table S3.1: Population characteristics of MOBI-Kids study and validation subgroup

	Validation study				MOBI-Kids study			
	Cases		Controls		Cases		Controls	
N	250		452		899		1910	
Age (mean, SD)	17.9 (3.8)		17.2 (4.1)		16.6 (4.3)		16.7 (4.3)	
Sex (female)	44.6%		45.8%		43.0%		43.5%	
Country	*N*	*%*	*N*	*%*	*N*	*%*	*N*	*%*
Australia	0	0.0	0	0.0	24	2.6	47	2.5
Austria	0	0.0	0	0.0	24	2.6	49	1.3
Canada	3	1.2	2	0.4	23	2.6	24	1.3
France	59	23.6	97	21.5	102	11.3	186	9.7
Germany	21	8.4	19	4.2	84	9.3	135	7.1
Greece	1	0.4	1	0.2	54	6.0	87	4.6
India	0	0.0	0	0.0	24	2.6	37	1.9
Israel	28	11.2	46	10.2	99	11.0	192	10.1
Italy	99	39.6	211	46.7	160	17.8	342	17.9
Japan	0	0.0	0	0.0	30	3.3	224	11.7
Korea	4	1.6	8	1.8	30	3.3	98	5.1
New Zealand	0	0.0	0	0.0	16	1.7	29	1.5
Spain	35	14.0	68	15.0	208	23.1	422	22.1
The Netherlands	0	0.0	0	0.0	21	2.3	38	1.9

3

CHAPTER 4

Recall of mobile phone usage and laterality in young people: the multinational Mobi-Expo study

Luuk van Wel *, Geertje Goedhart *, Chelsea E. Langer, Patricia de Llobet Viladoms, Joe Wiart, Martine Hours, Hans Kromhout, Geza Benke, Evdoxia Bouka, Revital Bruchim, Kyung-Hwa Choi, Amanda Eng, Mina Ha, Anke Huss, Kosuke Kiyohara, Noriko Kojimahara, Daniel Krewski, Brigitte Lacour, Andrea 't Mannetje, Milena Maule, Enrica Migliore, Charmaine Mohipp, Franco Momoli, Eleni Th. Petridou, Katja Radon, Thomas Remen, Siegal Sadetzki, Malcom Sim, Tobias Weinmann, Elisabeth Cardis, Martine Vrijheid, Roel Vermeulen.

** These authors contributed equally*

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Abstract

Objective To study recall of mobile phone usage, including laterality and hands-free use, in young people.

Methods Actual mobile phone use was recorded among volunteers aged between 10 and 24 years from 12 countries by the software app XMobiSense and was compared with self-reported mobile phone use at 6 and 18 months after using the application. The application recorded number and duration of voice calls, number of text messages, amount of data transfer, laterality (% of call time the phone was near the right or left side of the head, or neither), and hands-free usage. After data cleaning, 466 participants were available for the main analyses (recorded vs. self-reported phone use after 6 months).

Results Participants were on average 18.6 years old (IQR 15.2-21.8 years). Spearman correlation coefficients between recorded and self-reported (after 6 months) number and duration of voice calls were 0.68 and 0.65, respectively. Number of calls was on average underestimated by the participants (adjusted geometric mean ratio (GMR) self-report/recorded=0.52, 95% CI=0.47-0.58), while duration of calls was overestimated (GMR=1.32, 95%, CI=1.15-1.52). The ratios significantly differed by country, age, maternal educational level, and level of reported phone use, but not by time of the interview (6 vs. 18 months). Individuals who reported low mobile phone use underestimated their use, while individuals who reported the highest level of phone use were more likely to overestimate their use. Individuals who reported using the phone mainly on the right side of the head used it more on the right (71.1%) than the left (28.9%) side. Self-reported left side users, however, used the phone only slightly more on the left (53.3%) than the right (46.7%) side. Recorded percentage hands-free use (headset, speaker mode, Bluetooth) increased with increasing self-reported frequency of hands-free device usage. Frequent ($\geq$ 50% of call time) reported headset or speaker mode use corresponded with 17.1% and 17.2% of total call time, respectively, that was recorded as hands-free use.

Discussion Results indicate that young people can recall phone use moderately well, with recall depending on the amount of phone use and participants' characteristics. The obtained information can be used to calibrate self-reported mobile use to improve estimation of radiofrequency exposure from mobile phones.

Introduction

The rapid worldwide increase in mobile phone use has led to increased concern about potential health effects due to exposure to radiofrequency (RF) fields. Additionally, mobile phone use has changed dramatically in recent years with both the introduction of third and fourth generation cellular networks as well as continuously evolving smartphone hardware and software. Potential health effects (if they exist) related to RF fields originating from mobile phones would likely be greater among young people for various reasons. The neurological system of children is still developing and may be more sensitive to effects of RF, the distribution of RF absorption across the brain may be different compared to adults, and the specific absorption rate (SAR) in the most exposed part of the brain tend to be higher in children than it is in adults (1). Lastly, the lifetime exposure of children to RF from mobile phones will be larger as they start using a mobile phone at a young age compared to current adults. Several national and international bodies have recommended studies of exposure in childhood and adolescence as high priority RF research areas due to this (2). As a result, two large multinational case-control studies were set up, the CEFALO study in four (Northern) European countries (3), and the MOBI-Kids study in 14 countries, both within and outside Europe (4). In addition, several national studies were set up, including the HERMES study in Switzerland (5), and the SCAMP cohort study in the United Kingdom (6), looking at cognitive and behavioural outcomes.

Exposure assessment within epidemiological studies on health effects of mobile phone use generally relies on participants' recall of their mobile phone use. Previous validation studies among children and adolescents have found that this recall comes with substantial random and systematic errors (7-11), which can lead to under- or overestimation of the explored health risks (12-13). As part of MOBI-Kids, a case-control study exploring the potential effects of childhood and adolescent exposure to electromagnetic fields from mobile communications technologies on brain tumour risk (4), the Mobi-Expo validation study was performed to study recall of mobile phone use among young people from 12 out of 14 countries. This is the largest multinational validation study to date. A software application (app) was developed by Whist Lab (Paris, France) to be installed on participants' own smartphone or a study phone (8). In addition to duration and frequency of calls and text messages, the app also recorded information regarding laterality, hands-free usage, and data transfer. We report here the results of mobile phone usage and use behaviour recall at 6 and 18 months after the use of the app by study individuals. In addition, we explore if the observed differences in recall are related to demographic variables and/or phone usage.

Methods

From October 2012 to August 2014, volunteers between 10 and 24 years old were recruited in 12 MOBI-Kids countries: Australia, Canada, France, Germany, Greece, Israel, Italy, Japan, Korea, New Zealand, Spain and the Netherlands. The study was approved by the Institutional Review Boards in each country; all volunteers and/or their legal guardians provided informed consent following the country-specific protocols, including parental consent if indicated. More details about the recruitment procedures in each country are described in the paper by Langer *et al*. (14).

Participants

Two types of participants were enrolled in the study. The first type of participants were those who owned a smartphone using the Android operating system (OS) (60% of total study population). The second type (40%), who did not own a smartphone using the Android OS, received a study phone (either a Samsung Galaxy Mini or a Galaxy S2) for four weeks. These participants were instructed to insert their own SIM card into the study phone and use it just as they would use their own phone. All participants installed the XMobiSense application (app) on the smartphone. After four weeks of data collection, data were either automatically transferred to a server or a data file was created by the participant or study coordinator. Four countries only recruited participants who owned their own smartphone using the Android OS: Greece, Japan, Korea and New Zealand while the other eight countries recruited a mix of the first and second type of participants.

Recorded mobile phone use (XMobiSense)

Whist Lab (Paris, France) developed a smartphone app called "XMobiSense", which can be installed on any smartphone using the Android OS. This app records date, time, and duration (in seconds) of voice calls, laterality (right/left side) of use (hands-free while using a device (i.e.: wired headset, speaker mode, Bluetooth headset/car kit), and other hands-free without using a device (e.g., answering/ending a call)), number of text messages sent and received, amount of data transfer (in bytes), and the communication system and technology used for voice calls (2G/3G) and data transfer (WiFi, GPRS, EDGE, UMTS, HSDPA, and other). No personal information or call/text content was recorded by the app. After piloting the app and study protocol (8), some errors were observed in the recording of laterality and 'other hands-free use' for some devices. As such, only the following phone models were included in the current analyses on laterality and hands-free usage: Samsung Galaxy Ace, S (Plus), S2, S3, S3 (mini), S4, and S4 (mini).

Self-reported mobile phone use

Before participants started to use the app, a baseline questionnaire (Q1, 0 months) was completed (either face to face (64%), by phone (27%), or by (e)mail (9%)). The questionnaires included sociodemographic questions (parental education), and questions regarding current mobile phone use (frequency and duration of calls and number of text messages, laterality, hands-free use, proportion of use in urban/rural areas, sending e-mail, video, or files, hotspot and other data use, and voice over IP calling) over the past three months. Answers on questions concerning frequency and duration of mobile phone uses were collected as open-ended responses (e.g., minutes per day). The actual questionnaires can be found in the Supplementary Materials.
After the 4-week period of data collection by the app, participants who borrowed a study phone completed a change-of-use questionnaire (Q2, 1 month) upon returning the study phone either face to face (84%), by phone (14%), or by (e)mail (2%). Six months after data collection ended, a validation questionnaire (Q3, 6 months) was administered to both types of study participants by phone (76%), face to face (13%) or by (e)mail (11%). In this validation questionnaire, participants were asked to make an estimation of their mobile phone use during the 4-week period of data collection by the app. Questions included number and duration of voice calls, number of text messages sent, laterality (the side of the head one generally held the phone: left, right or both sides), hands-free device usage (wired headset, speaker mode of the phone, car kit, and/or Bluetooth headset), and time spent using the Internet. The question on number of text messages sent included both text messages (i.e., short messages service (SMS)) and WhatsApp messages in the baseline questionnaire. For Germany and Japan WhatsApp messages were also included in the Q3 questionnaires, but not for the other countries. As a result, these two countries were excluded from the analyses comparing self-reported to recorded number of text messages as the app did not record WhatsApp messages specifically as this was part of data use.

In five countries (Australia, Israel, Italy, Spain, and the Netherlands), the validation questionnaire was administered again at 18 months after using the app (Q4, 18 months) (face to face (4%), by phone (82%), by (e)mail (14%)). The study timeline can be found in Supplementary Materials Figure S4.4.

Study participation

A total of 587 participants used the XMobiSense application. 53 participants were excluded after errors were found in a substantial proportion of their call registration (i.e.: $>$5% of calls either had a duration of 0s or over 4h). An additional participant was excluded for having less than 8 days' worth of usable log files, bringing the number of included participants for our analyses to 533 (90.8% of recruited XMobiSense users). From these 533 participants, 466 (79.4%) successfully completed both the baseline questionnaire (Q1) and the validation questionnaire after 6 months (Q3) on the amount of calls and duration of calls. Among these, 190 also completed the questionnaire 18 months after using the app) (Supplementary Materials Figure S4.5). For the analyses on laterality and hands-free usage 229 participants who used phone models that performed accurately in laterality tests were included.

Statistical analyses

Volunteers with at least 8 days of usable XMobiSense log file data were included in the analyses. Recorded and self-reported number of voice calls and number of text messages sent were calculated per week, and duration of calls in minutes per week. Agreement between self-reported and recorded number and duration of calls and number of text messages sent was explored with Spearman correlations, Bland-Altman plots, and adjusted geometric mean ratios (self-reported/recorded). Multivariable analyses included the following covariates: country, age, gender, maternal educational level, type of phone user (type I: own phone vs. type II: borrowed study phone using their own SIM card), time period, and level of reported phone use. All covariates were used in one model for mutual adjustment and to calculate the adjusted geometric mean ratios. The maternal educational level was categorized into low (secondary/high school or less), medium (graduate of medium level technical/professional school), high (university/high level technical school or postgraduate university), and unknown. Recorded data transfer was calculated in megabytes (MB) per week, while self-reported total time spent using the Internet in minutes per week; the correlation between the variables was explored with the Spearman correlation. Recorded laterality (right/left side) and hands-free device usage (headset, Bluetooth, and speaker mode use) were calculated in percentages of total call time. Hands-free usage without a device (i.e.: regular call mode, but not near the head) was not included in hands-free usage as it usually represents the time between answering/ending a call and moving the phone to/from the head. The mean percentages of total call time were then derived for each category of self-reported laterality or hands-free device usage. Self-reported hands-free device users were divided into low (less than half the call time) and high (half or more of the call time) frequency users. Logistic regression analyses were performed to explore the influence of covariates on the agreement between self-reported and recorded laterality and hands-free device usage. All analyses were performed in SPSS Statistics Version 24.

Results

Participants were on average 18.6 years old (interquartile range 15.2 – 21.8 years), 37% were male, and 47% of the individuals' mothers had attained the highest level of education. The patterns in recorded mobile phone use are described in more detail by Langer *et al*., 2017 (14). In summary, higher recorded call number and duration were found among females, and in the oldest age group. Age and country explained a large part of the variance in recorded phone use characteristics, with gender, maternal education and study period explaining additional but smaller parts of the variance found.

Voice calls

The Spearman correlation coefficient between self-reported (after 6 months) and recorded number of voice calls was 0.68. On average, participants underestimated the number of calls made and received with a geometric mean ratio (GMR; self-reported to recorded) of 0.52 (95% confidence interval (CI) 0.47 to 0.58) (Table 4.1). As the recorded number of calls includes unsuccessful calls (i.e., no connection), while these are likely not included in the self-reported information, we performed a sensitivity analysis excluding potentially unsuccessful calls (defined as outgoing calls of 0 to 10 seconds) from the recorded information. This analysis resulted in a slight increase in the GMR to 0.59 (95% CI 0.53 to 0.66). Multivariable analyses showed that the ratio for number of calls significantly decreased with increasing age (i.e., younger children reported better than adolescents) and increased with increasing maternal educational level (Table 4.1).

Individuals who reported low mobile phone use underestimated their use, while individuals who reported the highest level of phone use were more likely to overestimate their use; this is also illustrated in the Bland-Altman plot, where the relative difference between self-reported vs recorded calls (y-axis) changes from a negative difference at lower levels to a positive difference at higher levels of self-reported use (x-axis) (Supplementary Materials Figures S4.1, S4.2, and S4.3). Individuals who used their own phone reported better than study phone users (Table 4.1). Furthermore, individuals from Greece and Korea had the highest underestimation of use, while individuals from Australia and Japan had the lowest underestimation of use (Table 4.1). The GMRs did not differ significantly by gender and time period (Table 4.1).
The Spearman correlation coefficient between self-reported (after 6 months) and recorded duration of time spent on voice calls was 0.65. The duration was on average overestimated by the participants with a GMR of 1.32 (95% CI 1.15 to 1.52) (Table 4.1). Excluding the potentially unsuccessful calls from the recorded information had no effect on the GMR. Multivariable analyses showed that the GMR significantly decreased with age, with an overestimation of call duration among the younger age groups (10-19y) and underestimation among young adults (20-24y) (Table 4.1). The GMRs significantly increased with maternal educational level (i.e., a lower educational level was linked to a better estimation) and with level of reported phone use, that is, individuals who reported high mobile phone use overestimated their use, and individuals reporting low phone use underestimated their use (Table 4.1) (illustrated in the Bland-Altman plot, Supplementary Materials Figure S4.1). The level of overestimation was higher for individuals who used their own phone compared to study phone users. Individuals from Japan, Australia, and Spain overestimated their time spent on voice calls most, while individuals from Greece, Israel and Korea were more likely to underestimate this. There was no significant difference in GMRs by gender and time period (Table 4.1).

Text messages

The Spearman correlation coefficient between self-reported and recorded number of text messages sent was 0.73. Participants on average overestimated the number of text messages they had sent (GMR=1.18; 95% CI 0.95-1.47) when recalling this after 6 months (Table 4.1). Multivariable analyses showed that the GMR significantly differed by country, with individuals from Spain and Greece having the highest level of overestimation, while individuals from Canada and

France underestimated the number of text messages sent (Table 4.1). Furthermore, overestimation was seen among individuals who reported sending a high number of text messages, while lower level users underestimated their number of text messages sent (see also Bland-Altman plot, Supplementary Materials Figure S4.1).

Recall

Comparing the recall among individuals who had questionnaires available from all three time points (before use (0 months), 6 and 18 months after use) showed an initial lapse in recall between the initial timepoint (GMR 0.64) and 6 months later (GMR 0.53), but relatively small differences between 6 months and 18 months (GMR 0.51) (Table 4.2). For both the number and total duration of calls the GMR at 6 and 18 months after use was slightly lower than the GMR at 0 months (comparing the baseline questionnaire versus the recorded data in the month thereafter). For number of text messages sent the GMR was somewhat lower at 18 months compared to 6 months after use; comparison with the GMR at 0 months was not possible, as text messages in the baseline questionnaire included WhatsApp messages. Recall at 6 and 18 months was focused on mobile phone use during the data collection period, while the baseline (0 months) interview focused on the three months beforehand. Although these are differing recall periods, we assumed that mobile phone use during the three months before data collection is representative for the data collection period

Data use

We observed a Spearman correlation coefficient of 0.39 between self-reported (after 6 months) time spent using the Internet and recorded amount (bytes) of data transferred. About 10% of the participants reported not having used the Internet, even though data transfer was recorded by the app. When looking at recorded amount of data, on average 72.5% (IQR 53.2%-99.1%) was transferred over WiFi.

Laterality

When comparing self-reported and recorded laterality, analyses were performed with and without the recorded call time where the phone was away from the head (Table 4.3). The latter analysis was included to better illustrate the comparison with self-reported laterality, where time away from the head was not

Table 4.1: Adjusted geometric mean ratio of self-reported (after 6 months) versus recorded number and total duration of calls and number of text messages sent (adjusted for the other variables in the table).

	Number of calls			Total duration of calls			Number of text messages sent		
	N	GMR[a]	95% CI	N	GMR[a]	95% CI	N	GMR[a]	95% CI
Overall	**466**	**0.52**	**0.47-0.58**	**466**	**1.32**	**1.15-1.52**	**422**	**1.18**	**0.94-1.47**
Country									
Australia	29	0.88	0.59-1.29	29	2.74	1.66-4.54	28	1.57	0.70-3.52
Canada	32	0.60	0.43-0.83	32	1.27	0.82-1.95	32	0.43	0.21-0.89
France	42	0.41	0.30-0.58	42	1.16	0.75-1.79	42	0.45	0.22-0.92
Germany	15	0.49	0.32-0.76	15	1.09	0.62-1.91	*na*[b]	*na*	*na*
Greece	41	0.31	0.21-0.48	41	0.56	0.33-0.96	41	2.46	1.06-5.73
Israel	38	0.40	0.29-0.55	38	0.89	0.60-1.33	35	1.52	0.81-2.85
Italy	56	0.38	0.29-0.52	56	1.07	0.73-1.58	55	0.76	0.40-1.46
Japan	22	0.96	0.64-1.43	22	3.61	2.16-6.04	*na*[b]	*na*	*na*
Korea	49	0.34	0.25-0.46	49	0.71	0.48-1.05	48	0.99	0.52-1.87
New Zealand	19	0.61	0.36-1.05	19	1.05	0.52-2.14	19	0.83	0.27-2.54
Spain	45	0.61	0.45-0.82	45	2.52	1.71-3.71	45	4.34	2.22-8.48
The Netherlands	78	0.65	0.50-0.84	78	1.78	1.27-2.50	77	1.69	0.97-2.92
		P<.01[c]				P<.01[c]		P<.01[c]	
Age									
10-14 years	109	0.72	0.60-0.85	109	2.22	1.77-2.78	104	1.27	0.90-1.79
15-19 years	166	0.50	0.43-0.58	166	1.32	1.09-1.59	154	1.14	0.85-1.54
20-24 years	191	0.40	0.34-0.46	191	0.79	0.67-0.95	164	1.13	0.83-1.53
		P<.01[c]			P<.01[c]			P=.87[c]	
Gender									
Male	175	0.54	0.47-0.62	175	1.43	1.19-1.71	159	1.31	0.98-1.75
Female	291	0.51	0.45-0.57	291	1.23	1.04-1.44	263	1.06	0.82-1.38
		P=.41[c]			P=.14[c]			P=.21[c]	
Maternal education									
Low	99	0.49	0.41-0.59	99	1.24	0.98-1.55	88	1.30	0.91-1.86
Medium	113	0.60	0.51-0.71	113	1.50	1.21-1.86	100	1.14	0.80-1.61
High	219	0.62	0.54-0.71	219	1.69	1.42-2.01	209	1.04	0.82-1.32
Unknown	*35*	*0.41*	*0.31-0.53*	35	0.98	0.69-1.38	25	1.26	0.67-2.35
		P<.01[c]			P=.01[c]			P=.74[c]	
Type of phone user									
Study phone	184	0.43	0.37-0.50	184	1.13	0.92-1.38	178	1.00	0.74-1.36
Own phone	282	0.63	0.55-0.72	282	1.55	1.31-1.84	244	1.39	1.03-1.87
		P<.01[c]			P=.01[c]			P=.12[c]	
Time period of recruitment									
Oct 2012 – Mar 2013	105	0.47	0.36-0.61	105	1.03	0.73-1.45	101	0.94	0.53-1.67
Apr – Sep 2013	105	0.47	0.37-0.60	105	1.17	0.85-1.61	94	1.89	1.08-3.33
Oct 2013 – Mar 2014	200	0.52	0.43-0.62	200	1.37	1.08-1.74	171	1.40	0.92-2.12
April – July 2014	56	0.64	0.41-1.02	56	1.86	1.02-3.38	56	0.77	0.31-1.93
Level of reported mobile phone use[d]									
<20th percentile	87	0.21	0.17-0.25	87	0.34	0.27-0.43	91	0.21	0.14-0.32
20th-40th percentile	68	0.32	0.26-0.39	102	0.75	0.59-0.94	84	0.65	0.43-0.98
40th-60th percentile	90	0.50	0.42-0.60	87	1.29	1.01-1.64	81	1.36	0.93-1.97
60th-80th percentile	115	0.79	0.67-0.93	98	2.37	1.87-2.99	83	2.30	1.55-3.43
>80th percentile	106	1.50	1.24-1.80	92	5.24	4.08-6.70	83	5.29	3.53-7.94
		P<.01[c]			P<.01[c]			P<.01[c]	

[a] Adjusted geometric mean ratio (GMR) of self-reported to recorded information (adjusted for other variables in table).
[b] Number of self-reported text messages not applicable for Germany and Japan, as it included WhatsApp messages.
[c] P-values of F-ratio indicating whether the mean values differ.
[d] Median number of calls/level: <20th: 1.9 calls/wk; 20th-40th: 4.6; 40th-60th: 8.8; 60th-80th: 19.7; >80th: 69.5.
Median duration of calls/level: <20th: 4.7 min/wk; 20th-40th: 15.9; 40th-60th: 43.8; 60th-80th: 109.7; >80th: 391.0.
Median nr of text messages/level: <20th: 0.7 p/wk; 20th-40th: 4.9; 40th-60th: 17.8; 60th-80th: 64.3; >80th: 398.4.

included as an option in the questionnaire. When considering only the call time

Table 4.2: Geometric mean ratio of self-reported versus recorded number and total duration of calls, and number of text messages sent, by time of self-report.

		Time of self-report					
		Before (0 months)		After 6 months		After 18 months	
	N[a]	GMR	95% CI	GMR	95% CI	GMR	95% CI
Number of calls	190	0.64	0.56-0.73	0.53	0.46-0.61	0.51	0.44-0.59
Total duration of calls	190	1.64	1.40-1.92	1.44	1.21-1.72	1.43	1.20-1.71
Text messages	167	*na*[b]	*na*[b]	1.10	0.87-1.40	0.94	0.72-1.24

[a] Included only individuals who had questionnaire data available for all three (or two in the case of text messages) time points.
[b] Text messages from baseline questionnaire (0 months) included WhatsApp messages.

close to the head, self-reported right-side users (at 6 months) actually used the phone on average for 70.8% of the call time on the right side of the head, while self-reported left side users used it for only 53.3% on the left side of the head. Participants who reported using the phone on both sides of the head actually used it on average more on the right (56.6%) than the left side (43.4%). Multivariable analyses showed that the level of recorded mobile phone use had a significant impact on the agreement between self-reported laterality at 6 months and recorded laterality (defined as $\geq$75% at the right or left side, otherwise both sides), with individuals in the $>$80th percentile of phone use having lower odds for agreement compared to individuals in the $<$20th percentile of phone use (odds ratio=0.48). Other covariates did not have a significant impact on the agreement (data not shown).
In addition, the consistency of self-reported laterality over time (before versus 6 and 18 months after using the app) is shown in Table 4.4. Participants who reported using the phone mainly on the right side of the head appeared to be most consistent in their report over time. Individuals who reported mainly left or both sides were more likely to shift over time.

Hands-free use

The recorded percentage of hands-free use increased with increasing self-reported frequency of hands-free device usage after 6 months (Table 4.5). For headset and speaker mode use, the recorded percentages of hands-free use significantly differed by self-reported usage levels. Among participants who reported no use of headset, speaker mode or Bluetooth in the questionnaire, recorded hands-free use was 3.2%, 3.8%, 0.2% of total call time, respectively. High frequent report ($\geq$50% of call time) of headset or speaker mode use (high frequent use was not reported for Bluetooth) corresponded to 17.1% and 17.2% of total call time, respectively, that was recorded as hands-free use.

4

Multivariable analyses showed no significant effect of explored covariates on the agreement between self-reported hands-free device usage at 6 months (no/yes) and recorded percentage hands-free use (no/yes, with yes being defined as $>$0.01% of total call time) (data not shown). When comparing self-reported hands-free device usage over time (before versus 6 and 18 months after using the app), participants who reported no (wired) headset or Bluetooth use were most consistent in their report over time (Table 4.6).

Table 4.3: Laterality: self-reported (after 6 months) versus recorded.

Self-reported	Recorded (% of total call time)			
	N (%)[a]	Mean % right side (SD)	Mean % left side (SD)	Mean % away from the head (SD)[b]
Mainly right side	158 (69.9)	58.8 (25.4)	22.7 (18.9)	18.5 (17.6)
Mainly left side	41 (18.1)	32.2 (23.7)	43.4 (28.5)	24.4 (28.6)
Both sides	27 (11.9)	41.2 (25.8)	32.5 (25.1)	26.3 (30.1)
Unknown	*3*			
Excluding % of total call time away from the head				
Mainly right side	158 (69.9)	70.8 (24.4)	29.2 (24.4)	-
Mainly left side	41 (18.1)	45.9 (27.8)	54.1 (27.8)	-
Both sides	27 (11.9)	56.6 (25.0)	43.4 (25.0)	-
Unknown	*3*			

[a] Included only phone models that accurately performed in the laterality tests. 3 individuals were missing self-reported laterality information, resulting in N=226.
[b] The phone was not near the head during a voice call, e.g., hands-free device usage, answering/ending a call.

4

Table 4.4: Laterality: self-reported compared over time (before, and after 6 and 18 months).

	Before (0 months)			
	Mainly right side, N (%)	Mainly left side, N (%)	Both sides, N (%)	Unknown N
After 6 months				
Mainly right side	119 (85%)	8 (26.7%)	8 (44.4%)	
Mainly left side	11 (7.9%)	22 (73.3%)	5 (27.8%)	
Both sides	10 (7.1%)	0 (0.0%)	5 (27.8%)	
Unknown				*2*
After 18 months				
Mainly right side	118 (84.3%)	6 (20.0%)	11 (61.1%)	
Mainly left side	9 (6.4%)	21 (70.0%)	2 (11.1%)	
Both sides	13 (9.3%)	3 (10.0%)	5 (27.8%)	
Unknown				*2*

Included only individuals who had self-reported laterality data available for all three time points (N=190).

Table 4.5: Hands-free device usage: self-reported (after 6 months) versus recorded.

Self-report	Recorded (% of total call time)		
Headset (wired)	N (%)[a]	Mean % headset use (SD)	P[b]
No	173 (76.2)	3.2 (10.0)	<.01
Yes, low frequency	43 (18.9)	8.5 (15.6)	
Yes, high frequency	11 (4.8)	17.1 (22.8)	
Speakermode	N (%)[a]	Mean % speaker mode use (SD)	P[b]
No	139 (61.2)	3.8 (80)	<.01
Yes, low frequency	75 (33.0)	9.7 (12.5)	
Yes, high frequency	13 (5.7)	17.2 (17.4)	
Bluetooth (headset, car kit)	N (%)[a]	Mean % Bluetooth use (SD)	P[b]
No	216 (95.2)	0.2 (1.7)	.19
Yes, low frequency	11 (4.8)	0.9 (2.9)	
Yes, high frequency	0 (0)	-	

[a] Included only phone models that performed accurately in the laterality tests. 2 individuals were missing self-reported information, resulting in N=227.
[b] P-values of F-ratio indicating whether the mean values differ.

Table 4.6: Self-reported hands-free device use compared over time (before, after 6 and 18 months).

	Before (0 months)					
	Headset		Speaker mode		Bluetooth	
	No N (%)	Yes N (%)	No N (%)	Yes N (%)	No N (%)	Yes N (%)
After 6 months						
No	116 (86.6%)	24 (46.2%)	81 (74.3%)	35 (43.8%)	174 (98.3%)	4 (77.8%)
Yes	18 (13.4 %)	28 (53.8%)	28 (25.7%)	45 (56.3%)	3 (1.7%)	2 (22.2%)
Unknown	*4*		*1*		*4*	
After 18 months						
No	112 (86.6%)	26 (50.0%)	71 (74.3%)	29 (43.8%)	172 (98.3%)	6 (66.7%)
Yes	22 (16.4%)	26 (50.0%)	38 (34.9%)	51 (63.8%)	5 (1.7%)	3 (33.3%)
Unknown	*4*		*1*		*4*	

Included only individuals who had questionnaire data available for all three time points (N=190).

Discussion

This large, multinational study on recall in young participants compared self-reported mobile phone use with software application-recorded mobile phone use. Recall errors were found for both number and duration of voice calls, with ratios significantly differing by country, age, educational level, and level of reported phone use, but not by time of interview. Systematic errors were found, with the number of calls underestimated by a factor of 0.52 on average, and the duration of calls and number of text messages sent overestimated by factors of 1.32 and 1.18, respectively. Individuals with low mobile phone use tended to underestimate their use, while individuals with the highest level of mobile phone use were more likely to overestimate their use. In addition, substantial random error was found, which is likely to affect risk estimates.

Previous validation studies among young people observed an overestimation of duration of calls, although the level of overestimation differed between studies (6-8,10). Earlier findings with regard to recall of number of calls among young people are less consistent: Aydin *et al*.(7) compared operator records with self-reports and found that individuals overestimated the number of calls, while the SCAMP study found an underestimation of call frequency (6). Other studies using software-modified phones (SMP) reported, as we do, an underestimation, the magnitude of which differed however (8-10). A study applying the same methods as the current study, among adults, found a significant but smaller underestimation of number of calls (GMR=0.65), and a smaller non-significant overestimation of duration of calls (GMR=1.11) (15). The Interphone validation study, among adults, found that individuals on average slightly underestimated the number of calls (GMR=0.92) while duration of calls was overestimated (GMR=1.42) (16). One previous study compared estimated versus billed text messages, and observed - in line with our results - that the number of text messages was on average overestimated (11).

We observed differences in recall by country, age, maternal educational, and amount of reported phone use. Differences by country were not observed in the CEFALO validation study (2 countries) (7), but were seen in the Interphone validation study among adults (11 countries; (16). In the current study, where, as in Interphone, the same protocol and software app were applied in each country, we cannot easily explain the different ratios between self-reported and recorded use (ranging from 0.31 to 0.96 for number of calls and from 0.56 to 3.61 for duration of calls) found between the countries, other than cultural differences in the way people recall their use. It might be important to take these differences into account in future studies.

In young people, differences in recall by age, with a higher ratio among younger ages, were also seen by Kiyohara *et al*. (10). The CEFALO validation study, however, found a higher ratio among the older age group (15-19 vs. 7-14 years) (7). The impact of maternal education level on recall has not been shown before.

Previous studies consistently observed a significant effect of the amount of phone use on recall, showing an increasing ratio with higher levels of reported phone use (10,15-16) or a decreasing ratio with higher levels of recorded phone use (7,11). While these systematic recall errors could have important implications for the risk estimates in epidemiological studies exploring potential health risks from mobile phone use, simulations have shown that the large amount of random errors observed in these studies will have an even larger impact (13).

The transfer of data via a smartphone has been increasing rapidly in the past years, especially with the rise of WiFi connections. It could therefore be important to include data transfer in future models estimating RF from mobile phone use. While our results showed that on average 72.5% of data was transferred via WiFi connection, this may well change with the rise of fast and affordable mobile data. RF exposure from data transfer depends on several factors, including the number of bytes transferred and the type and speed of the data connection. As these factors cannot be reported by participants, we asked the participants instead to estimate the time spent using the Internet on their smartphone. Time spent on the Internet, however, is a poor description of data sent since, for example email, surfing the Internet and Voice over IP connections imply very different amounts of data sent, and thus different RF exposures. It is therefore not surprising that we observed a poor correlation (r=0.39) between self-reported time spent using the Internet and the recorded number of bytes transferred. Furthermore, the observation that a small amount of data transfer was also recorded for participants who reported no data use implies that people probably are unaware of some of their data use, likely due to applications (e.g., push/pull technology) that run in the background. The impact of the relatively poor estimation of data transfer in epidemiological studies on brain tumour risk from mobile phone might, however, not be as important as voice calls, as the source of exposure is farther away from the head than it is when using the phone for calling, hence exposure levels are much lower. Similarly, using hands-free devices may lower exposure levels by having the phone as source of exposure farther away from the head.

Laterality is an important factor for case control studies exploring brain tumour risk from mobile phones: the location of the mobile phone relative to the head (e.g., left side vs right side) influences the region where most RF exposure is (1,17). The recorded data on laterality provided new and valuable insights in the patterns and validity of self-reported laterality. Two previous studies examining laterality among young people found some agreement (kappa(κ)=0.3 (19), κ=0.2 (10)) between self-reported and recorded laterality. They did not, however, report the actual percentages of time that the phone was held on the right and/or left side of the head, which can be used to adjust RF exposure estimations on either side of the head. We observed that the majority of participants consistently reported using the phone mainly on the right side of the head. Participants who reported right side use after 6 months actually used the phone for 71% (excluding call time away from the head) on the right side of the head. This percentage is lower than previously observed among adults (81%) (15) and quite a bit lower than the 90% assumed in the Interphone study (18). Self-reported left side users were more inconsistent, both in their report over time (i.e., only about half of the self-reported left side users at 6 months also reported left side use at 0 or 18 months) and compared to the recorded percentage of call time the phone was actually used on the left side of the head, which was only 54% on average. The study by Kiyohara *et al*. (10) also found a lower agreement of self-reported vs. recorded left side use compared to right side use. Participants who reported using the phone on both sides of the head were most inconsistent in their report over time, and the recorded laterality reflected somewhat more right (57%) than left side (43%) use of the phone. While we observed an inverse association between amount of phone use and the agreement between self-reported and recorded laterality, this was not observed by Kiyohara *et al*. (10). Our results indicate that young people, compared to adults, tend to use their phone more frequently on both sides of the head, especially self-reported left and both side users. So far, epidemiological studies on brain tumour risk from RF accounted for laterality, in the way that a potential risk was mainly expected on the side of the head the phone was primarily held (ipsilateral exposure) (20). Our observations, however, imply that accounting for laterality could be less informative when studying young people, as they are frequently exposed on both sides of the head. Certainly, the assumption of 90% ipsilateral use as used in the INTERPHONE study would not hold for current studies among young adults.

The agreement between self-reported and actual hands-free usage among young people has not been studied before. In comparing the self-reported use of hands-free devices over time, we noticed that participants who reported not using hands-free devices, would still show a small amount of recorded hands-free device use (0.2-3.8% of total call time). A higher reported frequency (half of the call time or more) of wired headset or speaker mode use agreed with a higher recorded percentage of call time (17.2-17.1%) in which these devices were used compared to low frequent reporters (8.5-9.7%). Nonetheless, these percentages were much lower than assumed before in the INTERPHONE study among adults (less than half of the call time, i.e., low frequent use: 0-25%, half or more of the call time, i.e., high frequent: 50-100%) (18). In contrast to several validation studies using operator records (7), the information recorded by the software app on number and frequency of voice calls was complete for the individuals included in the analyses; furthermore, the app also recorded information on laterality and hands-free usage. Although the period of recall in this study, at least for a subsample, was longer than in previous SMP-studies (8-10), operator records often go even further back in time (7), which is useful in the context of case-control studies on brain tumour risk that have to account for a certain latency period. Our sample mainly consisted of healthy and motivated volunteers, making it less comparable to participants of a case-control study; the recall of cases may be worse as they may suffer from physical and/or psychological impairments. Nonetheless, a big strength of our study was the fact that nearly two-thirds of our participants downloaded the app on their own smartphone instead of using a study phone, thereby better reflecting normal phone use behaviour and less awareness of being observed (i.e., the so-called Hawthorne effect (21)).

Conclusion

In conclusion, we compared software-recorded mobile phone use with recall after 6 and 18 months. Agreement between reported and measured number of calls and duration of calls was moderate; systematic errors were observed, with number of calls being underestimated on average and duration of calls and number of text messages sent overestimated. We note that there was also substantial random error, which is likely to have a major effect on risk estimates. The recall errors observed in this study for voice calls, laterality and hands-free use will provide important input for the development of the RF exposure model based on self-reported mobile phone use within the MOBI-Kids case-control study.

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Declarations of interest

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Supplementary Materials

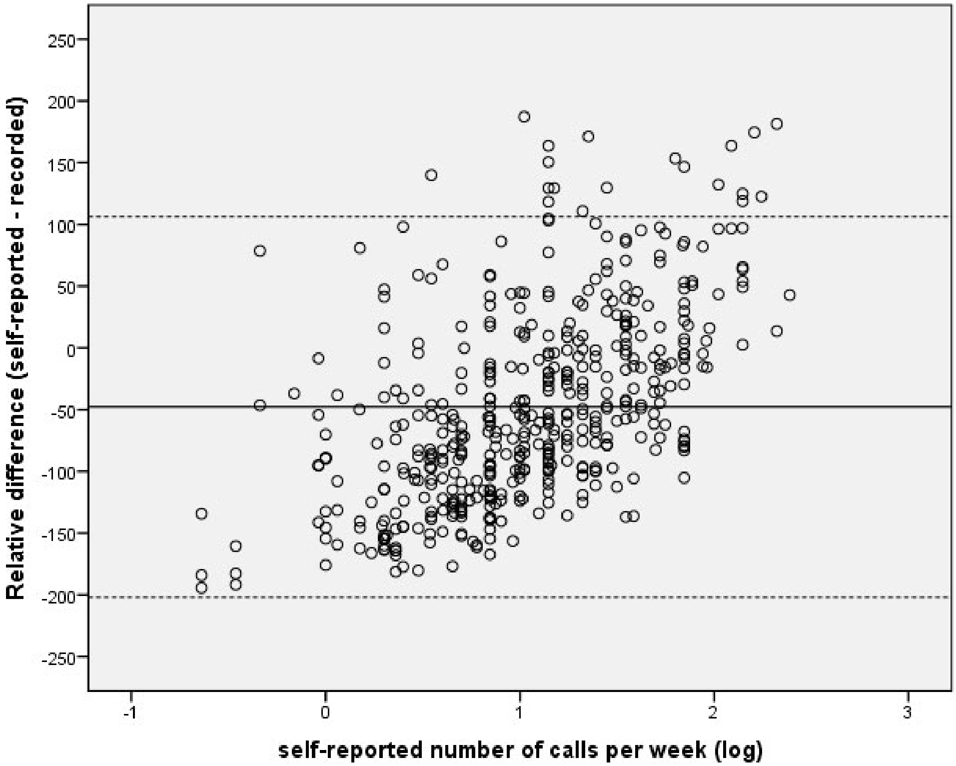

Figure S4.1: Bland-Altman plot for number of calls: relative difference between self-reported and recorded information against the self-reported information after 6 months (log transformed); lines indicate the mean and 95% limits of agreement.

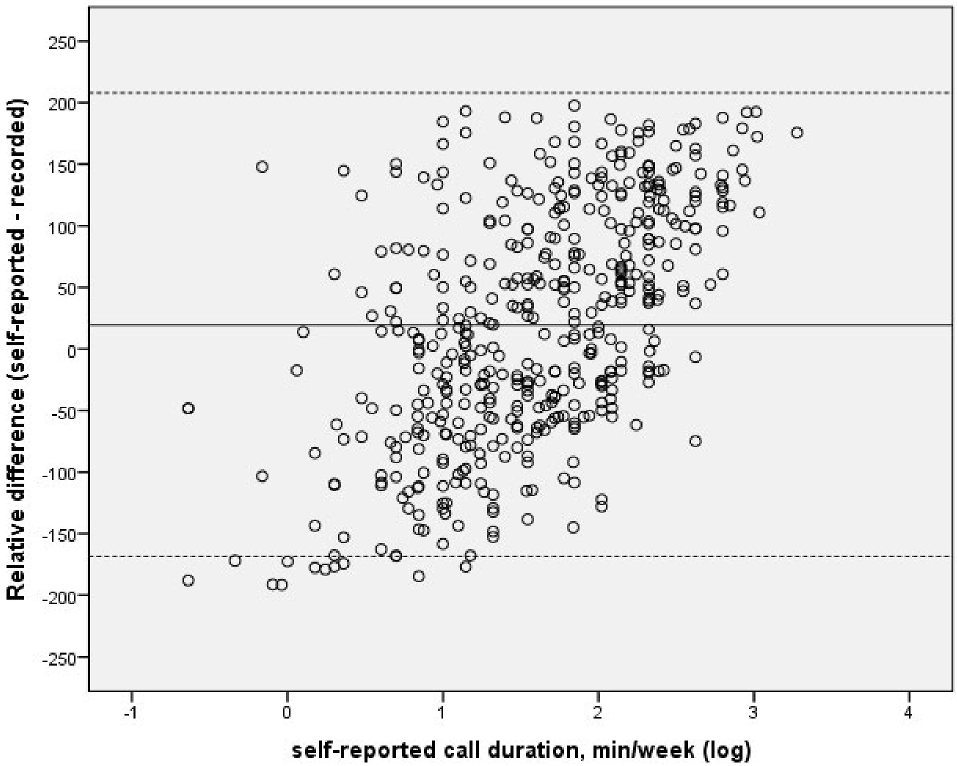

Figure S4.2: Bland-Altman plot for duration of calls: relative difference between self-reported and recorded information against the self-reported information after 6 months (log transformed); lines indicate the mean and 95% limits of agreement.

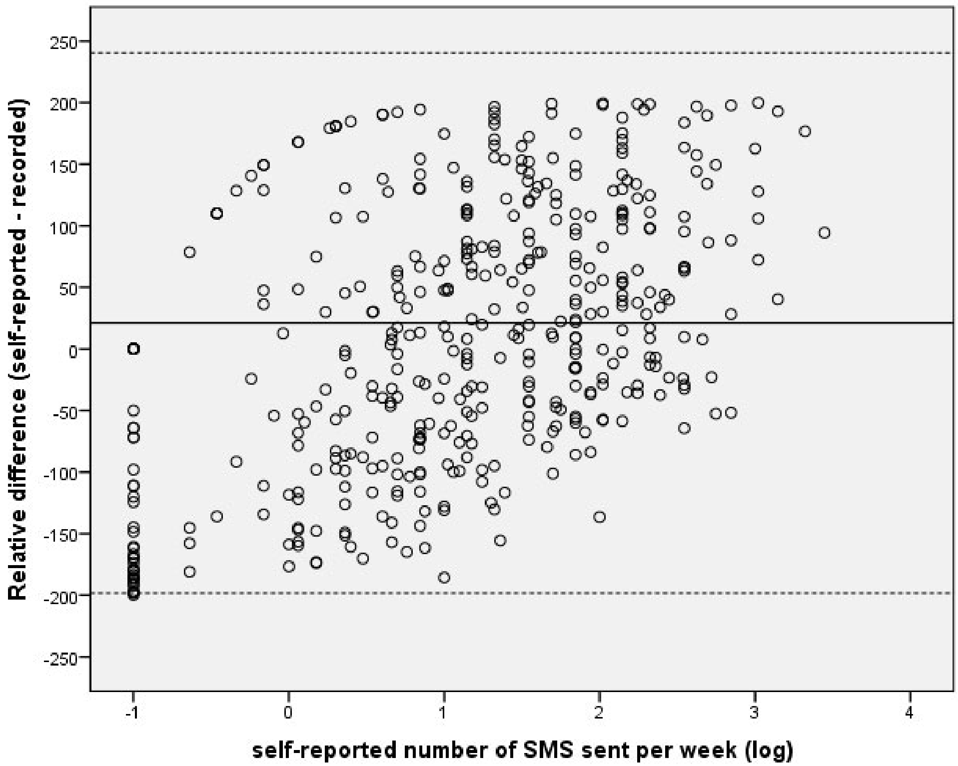

Figure S4.3: Bland-Altman plot for number of text messages sent: relative difference between self-reported and recorded information against the self-reported information after 6 months (log transformed); lines indicate the mean and 95% limits of agreement.

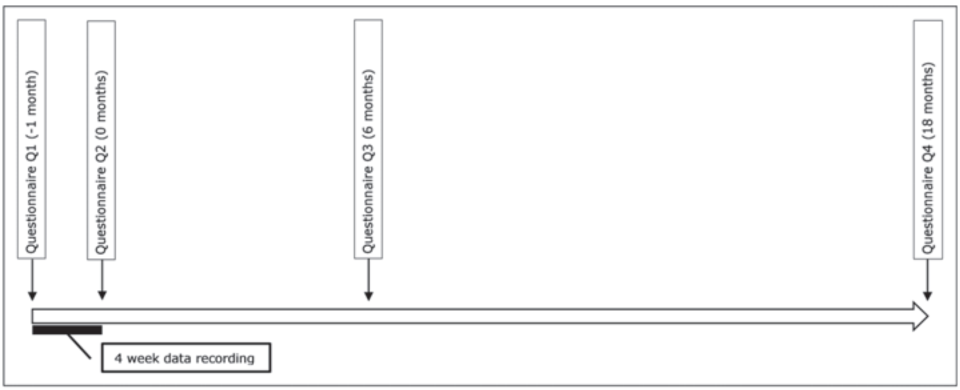

Figure S4.4: Study timeline. End of data recording period is defined as time 0.

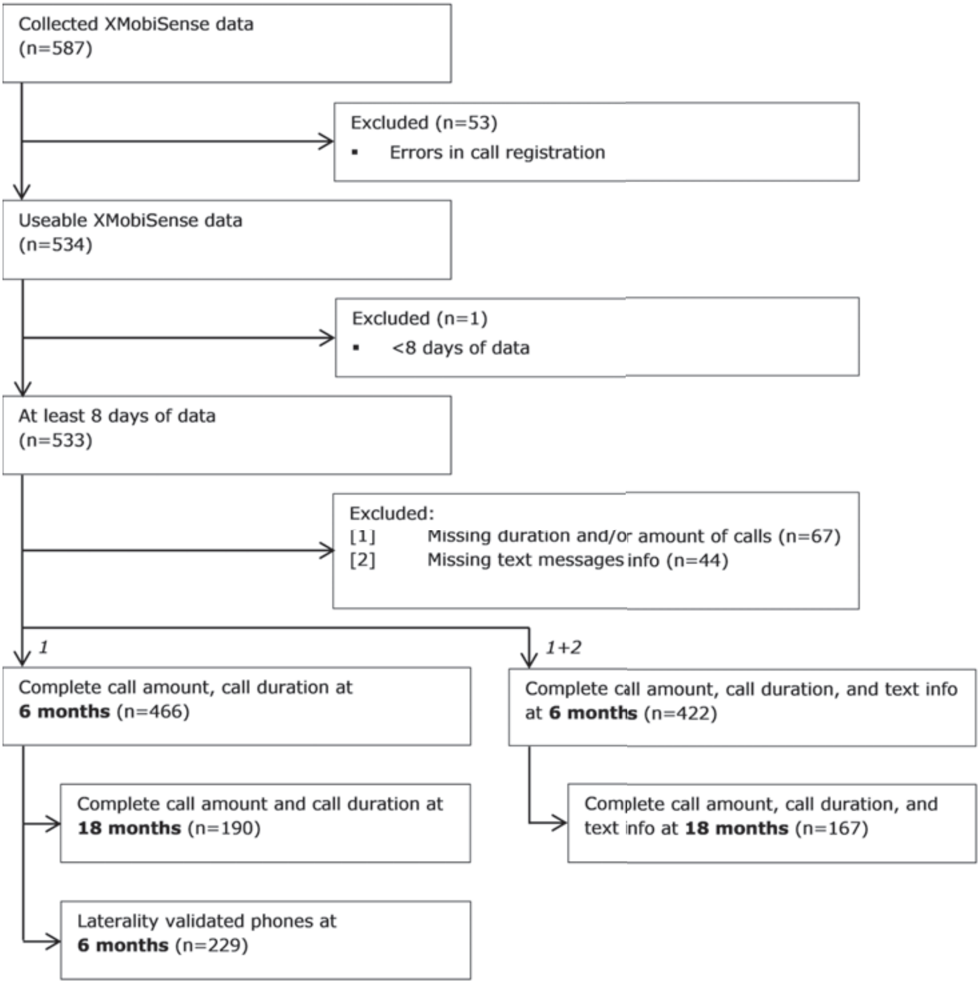

Figure S4.5: Study flowchart.

Table S4.1: Description of included participants in the main group (N=466) and the laterality sub-analysis (N=229).

Main group				
	Child age			
Country	10-14 year	15-19 year	20-24 year	Total
Australia	7	14	8	29
Canada	3	20	9	32
France	8	17	17	42
Germany	0	2	13	15
Greece	5	14	22	41
Israel	14	20	4	38
Italy	20	12	24	56
Japan	3	7	12	22
Korea	16	15	18	49
New Zealand	5	5	9	19
Spain	11	14	20	45
Netherlands	17	26	35	78
Total	109	166	191	466
Laterality sub group				
	Child age			
Country	10-14 year	15-19 year	20-24 year	Total
Australia	0	14	8	22
Canada	1	10	7	18
France	2	11	12	25
Germany	0	0	6	6
Greece	2	5	8	15
Israel	11	12	2	25
Italy	7	6	18	31
Japan	0	2	2	4
Korea	3	4	7	14
New Zealand	2	2	3	7
Spain	1	9	16	26
Netherlands	8	15	13	36
Total	37	90	102	229

Supplementary materials: questionnaires

I. Questionnaire Q1

MOBI-EXPO Screening Questionnaire & General Details

Study identification number FPrimary |__|__| - |8|8| - |__|__||__|__| - |__|__|
Country Phone's serial number Serial num

Date of interview: |__|__| / |__|__| / 20|__|__|
dd mm yy

Time of start of interview: |__|__|:|__|__|

Place of interview:
|1| home
|2| office
|3| telephone
|4| email/internet
|8| other, specify: ______________________________

General instructions:
**An effort to obtain accurate information to all questions should be performed. If subject still cannot recall the exact variable (e.g. for number of calls, etc.), please record range (when option is given). If eventually an unknown option must be recorded, please mark the option 'don't know' or |9|9| accordingly to the options given in the question.*

***In case of a proxy interview, please replace 'your' by 'your child's,' 'your grandchild,' or 'your husband/wife' or another appropriate phrase depending on the relationship of the proxy to the volunteer. Please adjust for proxy interview throughout the questionnaire.*

1

4

A. General details

A.1. What is your *(your child's)* name?

____
First Last

A.2. Could you tell me your *(your child's)* date of birth? |__|__|/|__|__|/|__|__|__|__|
dd mm yyyy

A.3. *Your (your child's) gender:*
|1| *male*
|2| *female*

A.4. Do you currently use a mobile phone at least once a week?
|0| no *(not eligible – stop here)*
|1| yes
|9| *don't know* *(not eligible – stop here)*

A.5. What is your *(your child's)* current address? ______________________________________
Home no. Street City

Postal Code: |__|__|__|__|__|__|__|__|__|

A.6. What is your *(your child's)* phone number? |__|__|__| - |__|__|__|__|__|__|__|

A.7. Mobile/cell phone number? |__|__|__| - |__|__|__|__|__|__|__|

A.8. E-mail Address? ____________________

A.9. Subject's/parents permission to contact the subject by phone:
|0| no
|1| yes

Signature: ______________________

A.10. Subject's/parents permission to contact the subject by e-mail:
|0| no
|1| yes

Signature: ______________________

2

A.11. What is the highest level of schooling that your mother has completed? *(Country specific)*

|1| secondary/high school graduate or less (less includes primary school)
|2| graduate of a medium level technical school or professional school
|3| graduate of university / high level technical school
|4| postgraduate university
|8| other, specify: ______________________
|9| *don't know*

A.12. What is the highest level of schooling that your father has completed? *(Country specific)*

|1| secondary/high school graduate or less (less includes primary school)
|2| graduate of a medium level technical school or professional school
|3| graduate of university / high level technical school
|4| postgraduate university
|8| other, specify: ______________________
|9| *don't know*

B. Mobile phone use: voice calls

B.1. What mobile phone calling plan do you currently use?

|1| voice only
|2| voice and data
|3| data only
|4| pre-paid card
|8| other, specify ______________
|9| *don't know*

B.2. Do you use an Android phone?

|0| no
|1| yes
|9| *don't know*

B.3. How often is your mobile phone used by other persons?

|1| (Almost) never
|2| Less than half of the time
|3| More than half of the time
|4| (Almost) always
|9| *don't know*

3

I would now like to ask you some questions about your mobile phone use over the last 3 months. Now I am interested in finding out how much you use your mobile phone. This includes both the number of calls you have made yourself, and the number of calls you have received. Note that I am interested only in voice calls for all of the following questions. Please do not count the time you spent using the SMS (text messages), internet, radio and game functions of your mobile phone and WiFi calls.

Number and duration of calls

B.4.1. What is the average number of calls you make and receive, per a typical day, week or month? You can give me a range, if that's easier.

B.4.1.1. |__|__| calls *or range* |__|__| calls **B.4.1.2.** |1| per day
|2| per week
|3| per month

B.4.2. What is the average length of time you spend making and receiving calls? You can answer in minutes or hours per a typical day, week or month. Again, you can give me a range, if that's easier.

B.4.2.1. |__|__| minutes *or range* |__|__| minutes **B.4.2.2.** |1| per day
|__|__| hours *or range* |__|__| hours |2| per week
|3| per month

Side of use (laterality)

B.5. When you use a mobile phone, do you generally use it on the right or left side of your head? (By generally we mean more than half of the time)
|1| right side
|2| left side
|3| both / either
|9| *don't know*

Use in an urban / rural area

B.6. When you use your mobile phone, could you tell me whether you use it:
|1| mainly in an urban area:
if yes, were most of these calls made |1-1| mainly (>50%) in the city center
|1-2| mainly (>50%) in suburban areas
|1-3| about half and half
|1-9| *don't know*
|2| mainly in a rural area
|3| both
|9| *don't know*

Hands-free devices and speakers

I would now like to ask you about hands-free device usage including headsets, and the speaker mode of your mobile phone for at least once a week for more than 3 months. *Please answer the next questions if you ever used hands free devices*

B.7. Do you use one of the following hands free devices such as: head set connected to the phone with a wire, the speaker mode of your phone, hands-free kit in a vehicle (not including Bluetooth headset)?	
|0| no *(go to B.9)* |1| yes |9| *don't know (go to B.9)*	
Have you used:	
Type of hands free device	**Use**
B.7.1. Head set connected to the phone with a wire	|0| no *(go to B.7.2.)* |1| yes |9| *don't know (go to B.7.2.)*
B.7.2. The speaker mode of your phone	|0| no *(go to B.7.3.)* |1| yes |9| *don't know (go to B.7.3.)*
B.7.3. Hands-free kit in a vehicle	|0| no |1| yes |9| *don't know*

B.8. **How often do you use one or more of the hands-free devices listed above as a proportion of your total call time?**

|1| almost never or rarely
|2| less than half the time
|3| about half the time
|4| more than half the time
|5| always or almost always
|9| *don't know*

B.9. **Do you use a Bluetooth headset?**

|0| no *(go to C.1.)*
|1| yes
|9| *don't know (go to C.1.)*

B.10. How often did you use the Bluetooth headset as a proportion of your total call time?

|1| almost never or rarely
|2| less than half the time
|3| about half the time
|4| more than half the time
|5| always or almost always
|9| *don't know*

C. Mobile phone use: other usages

Now, I would like to ask you about other usage of your mobile phones: (Skype, MSN, different technologies like text messages, internet etc.).
Please fill in the table by columns (when the answer is "no" or "don't know", please follow the relevant instructions).

		1.	2.	3.	4.	5.
		Sending Text messages	**Sending WhatsApps/Pings**	**Sending email, video, files with your phone or using the phone as a modem for your computer**	**Other data use (downloading music, movies, surfing the internet, online games, etc.)**	**(VoIP use, Skype, MSN or talk via wifi, including TalkieWalkie and Fring)**
C.1.	**Do you use this technology on your mobile phone?**	|0| no *(go to next column)* |1| yes *(go to C.2.)* |9| *don't know (go to next column)*	|0| no *(go to next column)* |1| yes *(go to C.2.)* |9| *don't know (go to next column)*	|0| no *(go to next column)* |1| yes *(go to C.2.)* |9| *don't know (go to next column)*	|0| no *(go to next column)* |1| yes *(go to C.2.)* |9| *don't know (go to next column)*	|0| no *(go to end)* |1| yes *(go to C.2.)* |9| *don't know (go to end)*
C.2.	**Amount of use** *If doesn't remember:* **you can give me a range**	|__|__| *range* |__|__| number of text messages sent Per |1| day |2| week |3| month	|__|__| *range* |__|__| number of messages sent Per |1| day |2| week |3| month	|__|__| *range* |__|__| |1| minutes ; |2| hours Per |1| day |2| week |3| month	|__|__| *range* |__|__| |1| minutes ; |2| hours Per |1| day |2| week |3| month	|__|__| *range* |__|__| |1| minutes ; |2| hours Per |1| day |2| week |3| month

6

Questions to interviewer:

D.1. *Who was interviewed? (Enter the relationship of the interviewee to the volunteer):*

|1| volunteer *(skip to D.3)*
|2| volunteer + mother
|3| volunteer + father
|4| volunteer + both parents
|8| other, please specify: ______________________

D.2. *Why did the volunteer not answer the questionnaire alone?*

|1| ethics requirements (volunteer not old enough to answer alone)
|2| volunteer could not remember the answer
|8| other, please specify: ______________________

D.3. *Was the interviewee responsive?*

|1| not at all (uninterested, reticent)
|2| fairly co-operative and responsive
|3| very co-operative, responsive and interested
|4| NA

II. Questionnaire Q2

MOBI-EXPO Changes in use Questionnaire

Study identification number FPrimary |__|__| - |8|8| - |__|__||__|__| - |__|__|
Country phone's serial number Serial num

Date of interview: |__|__| / |__|__| / 20|__|__|
dd mm yy

Time of start of interview: |__|__|:|__|__|

Place of interview: |1| home
|2| office
|8| other, specify: ______________________________

General instructions:

****In case of a proxy interview, please replace 'your' by 'your child's,' 'your grandchild,' or 'your husband/wife' or another appropriate phrase depending on the relationship of the proxy to the volunteer. Please adjust for proxy interview throughout the questionnaire.*

A. Mobile phone use: voice calls

A.1. When you were participating in the study, did you change your phone use at all (for example, number or duration of calls, the manner in which you used the phone, amount of data use, etc.)?

|0| no *(skip to end)*
|1| yes
|9| *don't know*

8

		1.	2.	3.	4.	5.	6.
		Number of calls	Length of time spent making and/or receiving calls	Side of head you generally use the phone on	Amount of time spent using the phone in urban versus rural area	Proportion of time spent using hands-free devices (i.e. speaker mode, headset, hands-free kit in a vehicle)	Proportion of time spent using Bluetooth headset
A.1.	Did you change your use compared to your regular phone usage?	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no |1| yes |9| don't know
A.2.	What was the change?	|1| more calls |2| less calls |9| *don't know*	|1| more time |2| less time |9| *don't know*	|1| more on the left side |2| more on the right side |3| both |9| *don't know*	|1| more in an urban area |2| more in a rural area |9| *don't know*	|1| higher proportion |2| lower proportion |9| *don't know*	|1| higher proportion |2| lower proportion |9| *don't know*

B. Mobile phone use: other usages

Now, I would like to ask you about other usage of the mobile phone: such as Skype, MSN, different technologies like text messages, internet etc.

		1.	2.	3.	4.	5.
		Sending Text messages	Sending WhatsApps/Pings	Sending email, video, files with your phone / using the phone as a modem for your computer	Other data use (downloading music, surfing the internet, online games, etc.)	VoIP use, Skype, MSN or talk via wifi (including TalkieWalkie and Fring)
B.1.	Did you change your use compared to your regular phone usage?	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no *(go to next column)* |1| yes |9| don't know *(go to next column)*	|0| no |1| yes |9| don't know
B.2.	Did you use this technology more or less often?	|1| more |2| less |9| *don't know*	|1| more |2| less |9| *don't know*	|1| more |2| less |9| *don't know*	|1| more |2| less |9| *don't know*	|1| more |2| less |9| *don't know*

9

4

III. Questionnaire Q3 and Q4 (6 and 18 months)

MOBI-EXPO Questionnaire

Characterization of conditions of use of mobile phones and exposure to radiofrequencies in a multi-centre epidemiologic study

Study identification number FPrimary |__|__| - |8|8| - |__|__||__|__| - |__|__|
Country phone's serial number Serial num

Date of interview: |__|__| / |__|__| / 20|__|__| Time of start of interview: |__|__|:|__|__|
dd mm yy

Place of interview:
|1| home
|2| office
|3| telephone
|4| email/internet
|8| other, specify: ______________________________

General instructions:
**An effort to obtain accurate information to all questions should be performed. If subject still cannot recall the exact variable (e.g. for number of calls, etc.), please record range (when option is given). If eventually an unknown option must be recorded, please mark the option 'don't know' or |9|9| accordingly to the options given in the question.*

***In case of a proxy interview, please replace 'your' by 'your child's,' 'your grandchild,' or 'your husband/wife' or another appropriate phrase depending on the relationship of the proxy to the volunteer. Please adjust for proxy interview throughout the questionnaire.*

A. Mobile phone use: voice calls

Number and duration of calls

I am interested in finding out how much you used the phone while participating in this study. This includes both the number of calls you made yourself, and the number of calls you received. By combining BOTH the calls you made and received, I can get some picture of your total phone use.
First, I am interested only in voice calls for all of the following questions. Please do not count the time you spent using the SMS (text messages), internet, radio and game functions of the mobile phone and WiFi calls.

When you were participating in the study:

A.1. What was the average number of calls you made and received per a typical day, week, or month? You can give me a range, if that's easier.

A.1.1.	|__|__| calls	*or range*	|__|__| calls	**A.1.2.**	|1| per day |2| per week |3| per month

A.2. What was the average length of time you spent making and/or receiving calls? You can answer in minutes or hours per day, week, or month. Again, you can give me a range, if that's easier.

A.2.1.	|__|__| minutes |__|__| hours	*or range* *or range*	|__|__| minutes |__|__| hours	**A.2.2.**	|1| per day |2| per week |3| per month

Side of use (laterality)

A.3. When you were participating in this study, did you generally use the phone on the right or left side of your head? (By generally we mean more than half of the time):

|1| right side
|2| left side
|3| both / either
|9| *don't know*

11

Use in an urban / rural area

A.4. When you were participating in the study, could you tell me whether you used the phone:

|1| mainly in an urban area:

if yes, **were most of these calls made** |1-1| mainly (>50%) in the city center
|1-2| mainly (>50%) in suburban areas
|1-3| about half and half
|1-9| *don't know*

|2| mainly in a rural area
|3| both
|9| *don't know*

Hands-free devices and speakers

I would now like to ask you about hands-free device usage including headsets, and the speaker mode of the mobile phone for at least once a week. *Please fill in the table if you ever used hands free devices*

A.5. When you were participating in the study, did you use one of the following hands free devices such as: head set connected to the phone with a wire, the speaker mode of your phone, hands-free kit in a vehicle (not including Bluetooth headset)?	
|0| no *(go to A.7)* |1| yes |9| *don't know (go to A.7)*	
Which of the following did you use:	
Type of hands free device	**Use**
A.5.1. Head set connected to the phone with a wire	|0| no *(go to A.5.2)* |1| yes |9| *don't know (go to A.5.2)*
A.5.2. The speaker mode of your phone	|0| no *(go to A.5.3)* |1| yes |9| *don't know (go to A.5.3)*
A.5.3. Hands-free kit in a vehicle	|0| no |1| yes |9| *don't know*

A.6. How often did you use one or more of the hands-free devices listed above as a proportion of your total call time?

|1| almost never or rarely
|2| less than half the time
|3| about half the time
|4| more than half the time
|5| always or almost always
|9| *don't know*

A.7. Did you use a Bluetooth headset while you were participating in the study?

|0| no *(go to B.1)*
|1| yes
|9| *don't know (go to B.1)*

A.8. How often did you use the Bluetooth headset as a proportion of your total call time?

|1| almost never or rarely
|2| less than half the time
|3| about half the time
|4| more than half the time
|5| always or almost always
|9| *don't know*

B. Mobile phone use: other usages

Now, I would like to ask you about other usage of the mobile phone: such as Skype, MSN, different technologies like text messages, internet etc.
Please fill in the table by columns (when the answer is "no" or "don't know", please follow the relevant instructions).

<table>
<tr><th></th><th></th><th>1.
Sending Text messages</th><th>2.
Sending WhatsApps/Pings</th><th>3.
Sending email, video, files with your phone or using the phone as a modem for your computer</th><th>4.
Other data use (downloading music, movies, surfing the internet, online games, etc.)</th><th>5.
(VoIP use, Skype, MSN or talk via wifi including TalkieWalkie and Fring)</th></tr>
<tr><td>B.1.</td><td>When you were participating in the study, did you use this technology on the mobile phone?</td><td>|0| no (go to next column)
|1| yes
|9| don't know (go to next column)</td><td>|0| no (go to next column)
|1| yes
|9| don't know (go to next column)</td><td>|0| no (go to next column)
|1| yes
|9| don't know (go to next column)</td><td>|0| no (go to next column)
|1| yes
|9| don't know (go to next column)</td><td>|0| no (go to B.3)
|1| yes
|9| don't know (go to B.3)</td></tr>
<tr><td>B.2.</td><td>Amount of use
If doesn't remember: you can give me a range</td><td>|__|__| range |__|__|
number of text messages sent
Per |1| day
|2| week
|3| month</td><td>|__|__| range |__|__|
number of messages sent
Per |1| day
|2| week
|3| month</td><td>|__|__| range |__|__|
|1| minutes ; |2| hours
Per |1| day
|2| week
|3| month</td><td>|__|__| range |__|__|
|1| minutes ; |2| hours
Per |1| day
|2| week
|3| month</td><td>|__|__| range |__|__|
|1| minutes ; |2| hours
Per |1| day
|2| week
|3| month</td></tr>
</table>

13

4

B.3. **Did other people use the phone for making and/or receiving voice calls?**
|0| no *(go to B.5)*
|1| yes
|9| *don't know (go to B.5)*

B.4. **What proportion of time did other people use the phone for making and/or receiving voice calls?**
|1| (almost) never
|2| less than half of the time
|3| more than half of the time
|4| (almost) always
|9| *don't know*

B.5. **Did other people use the phone for data (for example, sending emails, surfing the Internet, Skype, etc)?**
|0| no *(go to end)*
|1| yes
|9| *don't know (go to end)*

B.6. **What proportion of time did other people use the phone for data (for example, sending emails, surfing the Internet, Skype, etc)?**
|1| (almost) never
|2| less than half of the time
|3| more than half of the time
|4| (almost) always
|9| *don't know*

Questions to interviewer:

C.1. *Who was interviewed? (Enter the relationship of the interviewee to the volunteer):*

|1| volunteer ***(skip to C.3)***
|2| volunteer + mother
|3| volunteer + father
|4| volunteer + both parents
|8| other, please specify: ______________________________

C.2. *Why did the volunteer not answer the questionnaire alone?*

|1| ethics requirements (volunteer not old enough to answer alone)
|2| volunteer could not remember the answer
|8| other, please specify: ______________________________

C.3. *Was the interviewee responsive?*

|1| not at all (uninterested, reticent)
|2| fairly co-operative and responsive
|3| very co-operative, responsive and interested
|4| NA

15

CHAPTER 5

Organ-specific integrative exposure assessment: Radiofrequency electromagnetic field exposure and contribution of sources in the general population

Luuk van Wel, Ilaria Liorni, Anke Huss, Arno Thielens, Joe Wiart, Wout Joseph, Myles Capstick, Elisabeth Cardis, Roel Vermeulen.

Manuscript being prepared for submission

Abstract

Objectives In order to achieve an integrated radiofrequency electromagnetic fields (RF-EMF) dose assessment, detailed information about source-specific exposure duration and output power of these sources is needed. In this study, we developed the Integrated Exposure Model (IEM) to integrate the energy absorbed during exposure to predominant RF-EMF sources with exposure duration and output power for each source, and personal characteristics.

Methods The IEM used specific absorption rate (SAR) transfer algorithms developed within the project to estimate RF-EMF dose (mJ/kg/day) taking into account source specific attributes, personal characteristics, and usage patterns. Information on these was obtained from an international survey performed in four European countries (France, Netherlands, Spain, and Switzerland) with 1755 participants. Together with output power estimations for each source, the RF-EMF dose was estimated for 64 anatomical sites.

Results We obtained median whole-body and whole-brain doses of 183.7 mJ/kg/day and 204.4 mJ/kg/day, respectively. main contributors to whole-brain dose were use of mobile phone near the head for calling (using 2G networks) and far-field sources, whereas the latter together with multiple other RF-EMF sources were the main contributors for whole-body dose. For other anatomical sites 2G phone calls, mobile data, and far-field exposure were important contributors.

Conclusions We developed an IEM for RF-EMF that can provide insight into main contributors to total RF-EMF dose and applied it to an international survey, providing a snapshot of population RF-dose. It is an important tool to gain insights in future epidemiological studies, for risk assessment and exposure reduction strategies.

Model availability The model is available upon request: R.C.H.Vermeulen@uu.nl

Introduction

Radio-frequency electromagnetic fields (RF-EMF) are used extensively in modern society to facilitate wireless communication. This has led to health concerns regarding potential short and long-term effects of RF-EMF in the general population (1). An accurate exposure assessment including all major RF-EMF sources is required to address these concerns. Previously, self-reported device use, data from mobile phone network operators, and wave propagation models have been used to estimate exposure, methods often limited to one or a few RF-EMF sources (2–4). However, the proliferation of novel devices together with the continuing evolution and uptake of RF-EMF technologies have led to a rapidly expanding spectrum of sources that need to be considered, ranging from smartphones and wearables to WiFi networks and modern cellular base stations. In addition, for personal devices the patterns of use are often an important determinant in RF-EMF dose: a mobile phone held near the head during a phone call will result in a different exposure pattern compared to that induced by a tablet placed on the lap while streaming videos. In all, these aspects have made RF-EMF exposure assessment a daunting effort (5,6). Preferably, a series of realistic population exposure scenarios would be available for application in risk assessment and (if appropriate) risk mitigation, where relevant RF-EMF sources and the contribution of each to total exposure are included for various exposed groups. Well known sources include mobile phones, WiFi routers, and mobile phone base stations, as well as other modern communication devices such as tablets, fitness trackers, virtual reality glasses, bodyworn sensors and smart watches. An integrative model including multiple sources is therefore needed to estimate RF-EMF exposure in the population. (7) developed an exposure surrogate model combining near-field and far-field exposure. However, the devices included in this model were limited to mobile phones, DECT (Digital Enhanced Cordless Telecommunications) phones, and far-field sources and exposure was estimated only for the brain and whole body. This model does not include all current prevalent RF-EMF sources, technologies, and use patterns.

To close this gap, we designed an Integrated Exposure Model (IEM) to include many relevant current and near future sources, based on specific absorption rate transfer algorithms (SAR) developed by Liorni *et al.* (manuscript submitted) (8) within the French ANSES funded CREST project and the EC funded GERoNiMO project. The IEM was applied to a survey on mobile device use to estimate population RF-EMF exposure scenarios. This survey, held among the general population of four European countries (participants aged 18 years and older), asked detailed questions on the use of many telecommunication devices as well as the functions for which they are used. The results provide detailed estimates of population-wide exposure levels and the contribution of various RF-EMF sources to these levels, which can in turn be used as input for future epidemiological investigations, risk assessment, and exposure reduction strategies.

Methods

RF-EMF Integrated Exposure Model

The Integrated Exposure Model (IEM) estimates the integrated dose for multiple anatomical sites, including the whole body, different organs (brain, heart) and tissues and more specific locations (e.g., individual brain regions) in millijoules per kilogram per day (mJ/kg/day). This is based on exposure from near-field (the distance from the source is smaller than one wavelength), near-to-far-field (the distance from the source is larger than one wavelength and smaller than two wavelengths), and far-field (the distance from the source is larger than 2 wavelengths) RF sources. Dose is given per day but can be adjusted to any desired time period (e.g., dose per month) depending on the available input data. The model takes into account source specific attributes (source type, output power), personal characteristics (age, sex, body mass, height), and the way devices are being used (position relative to the body, type of use, duration of use), allowing for better dose estimation and insight in the contribution of different sources and uses to the total RF-EMF dose received.

The IEM is combines SAR estimates from the transfer algorithms (TA) developed by Liorni *et al.* (manuscript submitted) (8) for each RF source, which are combined with scenarios of use (in terms of time and output power emitted) to obtain a dose estimate per source per anatomical site. These dose estimations per RF source are then integrated into a single total dose per anatomical site. A total of ten RF sources have been included. Specifically, the near-field sources are mobile phone, DECT phone, tablet, laptop, body area network, smartwatch, on/near body device, virtual reality headset; the near-to-far-field sources are WiFi router and smart boxes for internet connection; and lastly the far-field sources (e.g. mobile base stations) are generically represented by plane-wave exposure. The integrated dose has been estimated for 64 unique anatomical sites by means of the IEM. The number of anatomical sites included per transfer algorithm differs with respect to the RF-sources analysed. In the current version of the model every source includes at least the anatomical whole-body and whole-brain. The

complete list of anatomical sites can be found in Figure S5.7 (Supplementary Materials).
Figure 5.1 shows the four steps of the model. In step 1, the input information falls into three main categories: [A] personal characteristics (age, sex, mass, height), [B] information concerning the use patterns (position, device function, duration of use), and [C] the output powers associated with those use patterns. In step 2, the personal characteristics are used as input for the SAR transfer algorithms. The information from the latter two categories is combined to create the scenarios of use, where each scenario specifies the complete use pattern (e.g., duration of a phone call, watching video, checking e-mail) and the output power during those uses. Step 3 consists of estimating the RF-EMF dose for each source based on the input information from the previous steps, and lastly in step 4, the estimated doses are integrated into one overall RF-EMF dose including all sources. This last step is repeated for each included anatomical site. The model was developed around a modular structure where each module consists of one RF-EMF source, allowing for easy addition of new sources in the form of new modules. Modules can be upgraded with new data when transfer algorithms for more anatomical sites are developed.

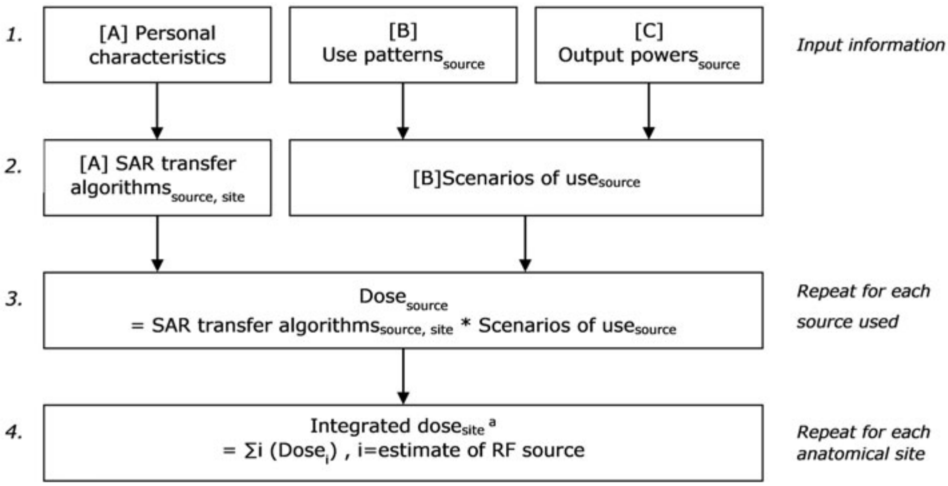

Figure 5.1: Distribution of trigger reasons. All triggered questionnaires on the left versus completed questionnaires on the right.

Step 1: Input information

Device use information in the population was obtained from the Mobile Device Use Survey, part of the CREST project (9). It was developed using LimeSurvey (LimeSurvey GmbH, Hamburg, Germany) and hosted on servers of Utrecht University in the Netherlands. Recruitment took place from October 2016 to April 2017 in four European countries: France, the Netherlands, Spain, and Switzerland. A random sample of 10,000 house addresses was taken in each country, resulting in 40,000 addresses overall. One invitation letter was then sent to each address detailing the survey and providing a website address together with a token to access the survey. One participant per household was asked to complete the survey. Responses from participants younger than 18 years were excluded from the results due to ethical constraints. Ethical approval was obtained in France, the Netherlands, Spain, and Switzerland. In the Netherlands, a small incentive was offered to increase participation (lottery of gift cards of 40 Euro). In Spain additional volunteers were requested from the research institute's volunteer program. The survey was available in Dutch, English, French, German and Spanish and contained detailed questions concerning the type of devices used, how long they were used and how they were mostly held during use, allowing for the creation of detailed scenarios of use in the IEM. Questions were grouped into five main categories: "About you", "Your use of mobile phones", "Your use of tablets", "Your use of laptops", and "Your use of other devices". Questions included the frequency and duration of use, number of devices used on a regular basis, and the use of mobile phones and tablets. For the latter two devices, we asked what people did on the devices (e.g., phone calls, streaming audio), the position in which the device was mainly held, the main location of use (i.e.: work, home, school, transit) and the frequency and duration of use of those functions. The complete questionnaire can be found in Supplementary Materials B. Each device, and -if available- function used on that device, was assigned an output power derived either from the literature or based on expert opinion (Table 5.1). The output power depends on the function it was used for, with heavy data transfer generally resulting in a higher output power. Values for the various mobile phone and tablet functions were obtained from average WiFi duty cycles determined by (10), assuming a network speed of 6 megabit per second (Mbps).

Additional input data

Most of the survey data used for population dose estimates was obtained from the Mobile Device Use Survey. As this survey contained no information on the use of DECT phones or on far-field exposure estimations, additional input information was obtained from other sources. Minutes of DECT calls per day were imputed using data from the AMIGO study where subjects were asked for the duration of DECT calls in minutes per week using a categorized question (11). The average value of each category was assumed and matched to participants based on age and sex. Far-field exposure information was obtained from the GERoNiMO personal exposure measurement survey in the form of time-weighted average exposures obtained over 24 to 72 hours per subject (12). Data was collected on 16 different frequency bands, in Switzerland, Slovenia, Spain, Denmark, and the Netherlands between September 2014 and February 2016. Swiss, Spanish, and Dutch results were used in each respective country. For French participants, the average over all five countries was used (Table 5.1). No details were available on the height and mass of the participants. Depending on the country the participant originated from, proxy data was used from Statistics Netherlands (CBS) (13), the Swiss Gesundheidsbefragung 2012 (14), and Special Eurobarometer 246 (15). Complete details on the height and mass proxies used can be found in Table S5.2 (Supplementary Materials). The IEM was designed to assess dose based on durations of use in minutes. As the survey contained categorical questions, the center point of each category was used as the duration in minutes. The top categories stating “more than x minutes” were multiplied by (5/3) to obtain an exact number of minutes (16). For some functions (e.g., texting) only the frequency of use was asked. A set amount of time was assumed for those functions based on estimations of the actual data transmission time involved. One SMS message was assumed to be 0.1 second of data transmission, one video message 10 seconds, uploading a photo or video 30 seconds, and streaming audio/video or playing an online game 300 seconds. The survey did not contain information concerning the presence of WiFi routers nearby the participant. It was assumed that each participant was in the near-to-far-field of a WiFi router for one hour per day, with an estimated average output power of 5 mW. European average network operator values were derived from the “Mobile Phone Operator Questionnaire” from the MOBI-Kids study (data not published) (2015). Based on this, 55% of all call minutes made by a participant was assumed to be spent on 2G network with the remaining 45% spent on 3G networks. The model could not include calls on 4G networks. Laterality (i.e., is the phone held on the left or right side of the head) was assumed to be 50% of the total time on each side of the head.

Step 2A: SAR transfer algorithms

Anatomical human models belonging to the Virtual Population (17) were used in simulations of induced SAR values. The SAR depends on the position of the source relative to the anatomical site, the output power of the source, the RF frequency used, and body morphology (e.g., body mass, tissue dielectric properties) (8). Antenna positions of various devices surrounding human models of different ages, sex, and BMI values were used to develop transfer algorithms for estimating the SAR when the body is exposed to different devices placed at various locations (8). The transfer algorithms require various input information, depending on the RF-source modelled. These include information on the subject's age, sex, mass, and height. The included models cover a body mass range from 18 to 120 kg. Uncertainty of SAR calculations strongly increases outside of these boundaries, therefore a subject's mass outside this range is reset to the lower or upper mass limit, respectively in the IEM. Transfer algorithms were modelled on specific frequency ranges. For most near-field RF sources this was 2450 MHz, while for far-field multiple frequency bands were included. Table 5.1 includes all frequencies used in the model per RF-source. The transfer algorithm for mobile phones and DECT phones near the head was based on the RF-EMF computational modelling performed in the MOBI-Kids study (18). The transfer algorithms assume an average position where the source device is held. Some of the included transfer algorithms have the additional option of specifying the position of the device near the body, namely for tablets, mobile phones, and body area networks. A complete list of these positions can be found in Table S5.1 (Supplementary Materials). The output power in the transfer algorithms was normalized to 1 Watt. As real RF sources often transmit at a power much lower than the nominal one, an adjustment for actual output power is made during the dose estimation. The exception here are the mobile and DECT phone transfer algorithms, in which output power was already taken into consideration during the SAR estimation by using average values per phone classes (18) and by incorporating adaptive power control (i.e., average percentage of phone's maximum output power while using particular technologies) values of 50% for 2G and 1% for 3G network calls (19).

Step 2B: Scenarios of use

The dose received by the anatomical sites is determined by [1] the position of the source relative to the anatomical site [2] the function used with the RF source and the corresponding actual output power, and [3] the associated time usage. The IEM allows for multiple output powers from the same RF source to be included, proportional to the time the source was used at a specified output power. Effectively this means that many different types of use of the same RF source can be included with their own output powers, e.g. to differentiate between uses such as SMS messages (i.e., low power) and video streaming (i.e., high power). This information is incorporated into the scenarios of use. Furthermore, for RF sources in which it is possible to specify a device position a specific scenario of use is assigned. These duration-output power (Watt * seconds) combinations are then multiplied, and the results are summed as follows:

$$Scenario\ of\ use_{source_i position_i} = \sum(duration_i * outputpower_i)$$

$$i = used\ function\ (e.g.\ phone\ call)$$

As an example, if a tablet is used throughout the day for web browsing for 600 seconds (10 minutes) at 1.6 mW, and for making a video call of 1800 seconds (30 minutes) at 5.4 mW, this would result in (600 * 1.6) + (1800 * 5.4) = 10680 mJ per day. This number is then corrected to the actual dose received at the anatomical site using the SAR estimations. Output power is expressed in Watts for near-field and near-to-far-field sources, with estimations of output powers belonging to certain device functions from either literature or expert opinion. For far-field estimations the power flux density (mW m^{-2}) is needed (e.g., a time-weighted value per day) which can be obtained either from exposimeter measurements (12) or 3D wave propagation models such as NISMAP (20).

Step 3 and 4: Integration of sources and dose estimation

The SAR predicted from the transfer algorithm for each specific anatomical site is then multiplied with their corresponding scenario of use to result in a dose per RF-source. When an RF source is not used by the subject, the dose for that specific source is set to zero. It is assumed that the separate sources are incoherent. This means that the doses relative to each RF source can be summed together (8).

Table 5.1: Estimated output powers for different sources, functions.

Near-field sources	Frequency (MHz)	Output power (mW)			
1. Mobile phone	-	-			
a. Calls near head, 2G	900/1800	*Not applicable* [a]			
b. Calls near head, 3G	900/1800/2100	*Not applicable* [a]			
c. Calls using hands-free kit	2450	45			
d. SMS messages	2450	0.01[c]			
e. Browsing internet	2450	1.6[c]			
f. Internet voice calls	2450	3.1[c]			
g. Internet video calls	2450	5.4[c]			
h. E-mail	2450	1.6[c]			
i. Voice messages	2450	3.1[c]			
j. Video messages	2450	5.4[c]			
k. Upload photo/video	2450	87.4[c]			
l. Streaming audio	2450	6.7[c]			
m. Streaming video	2450	81.4[c]			
n. Online games	2450	6.7[c]			
o. Use as a hotspot	2450	3.1[c]			
2. DECT phone	1800	-			
3. Tablet	-	-			
a. Browsing internet	2450	1.6[c]			
b. Internet voice calls	2450	3.1			
c. Internet video calls	2450	5.4			
d. E-mail	2450	1.6			
e. Voice messages	2450	3.1			
f. Video messages	2450	5.4			
f. Upload photo/video	2450	87.4			
g. Streaming audio	2450	6.7			
h. Streaming video	2450	81.4			
i. Online games	2450	6.7			
4. Laptop	2450	1			
5. Body Area Network	2450	0.05			
6. Smartwatch	2450	0.05			
7. On/near body device	2450	*No info*			
8. Virtual reality headset	2450	14.5			
Near-to-far-field sources	Frequency (MHz)	Output power (mW)			
9. WiFi router	2400	5			
Far-field sources	Frequency (MHz)	Power flux density (mW/m^2) [c]			
10. Far-field		France	Netherlands	Spain	Switzerland
a. FM radio	87.5 – 108	0.0266	0.0105	0.0675	0.0065
b. DVB-T	470 – 790	0.0054	0.0098	0.0096	0.0026
c. LTE800 downlink	791 – 821	0.0048	0.0129	0.0001	0.0017
d. LTE800 uplink	832 – 862	0.0023	0.0016	0.0001	0.0011
e. GSM900 uplink	880 – 915	0.0219	0.0148	0.0307	0.0166
f. GSM900 downlink	925 – 960	0.0331	0.0348	0.0580	0.0104
g. GSM1800 uplink	1710 – 1785	0.0135	0.0067	0.0097	0.0183
h. GSM1800 downlink	1805 – 1880	0.0143	0.0105	0.0269	0.0056
i. DECT	1880 – 1900	0.0025	0.0035	0.0054	0.0016
j. UMTS uplink	1920 - 1980	0.0083	0.0072	0.0138	0.0078
k. UMTS downlink	2110 – 2170	0.0108	0.0094	0.0147	0.0068
l. ISM 2.4GHz	2400 – 2485	0.0053	0.0076	0.0085	0.0037
m. LTE2600 uplink	2500 – 2570	0.0001	0.0000	0.0000	0.0000
n. LTE2600 downlink	2620 – 2690	0.0006	0.0007	0.0002	0.0005
o. WiMax 3.5GHz [e]	3400 – 3600	-	-	-	-
p. ISM 5.8GHz [e]	5150 – 5875	-	-	-	-

[a] Transfer algorithm incorporated output power in SAR estimations.
[b] Joseph *et al.*, 2013.
[c] Eeftens *et al.*, 2018.
[d] No data available on these frequency bands.

Statistical analysis

RF-EMF dose estimations for all participants of the population survey were obtained using the IEM. From this sample of individual dose estimations, the median, mean, 5th, and 95th percentiles were used to provide insight into the dose as well as the spread within the population. Results were stratified for age, sex, and country of origin. Relative contributions of individual sources to total integrative dose were calculated per participant and consequently shown as percentile distributions using boxplots. All calculations are shown for whole-body and whole-brain sites. The model was written in the open source programming language R and a package is available upon request. All analyses were performed using R version 3.4.1. (21).

Sensitivity analyses

As there was no information on the amount of time spent in range of a near-to-far-field of a WiFi router, we assumed one hour of exposure for each participant. Two sensitivity analyses were performed to assess the influence of this assumption. In the first analysis [1] half an hour of exposure (50%) was assumed instead, and in the second analysis [2] two hours of exposure (200%) was assumed.

Results

Mobile Device Use Survey

A total of 1755 participants from four countries completed the survey (Switzerland 388 (22.1%); Spain 321 (18.3%); France 478 (27.2%); the Netherlands 568 (32.4%)). The number of male and female respondents was nearly identical, with 49.2% women and 50.8% men. The average age was 54 years (range 40-65 years), and 6.9% were 25 years or younger and 22.6% older than 65 years. The complete age distribution can be seen in Figure S5.6 (Supplementary Materials). A total of 1223 (69.6%) of participants obtained a college level or higher education.

Device use

Mobile phones, laptops, and tablets were the three devices most used by study participants. The vast majority of participants reported using a mobile phone at least once during the last three months (96.7%), followed by a laptop (66.5%)

and tablet (56.5%). The use of other devices was significantly less common: activity trackers were used by 4.9% of all respondents, smartwatches by 3.1%, body worn sensors (i.e., body area networks, medical sensors) by 2.1%, and virtual reality headsets by 1.8%. The duration of use varied between devices, with laptop use, tablet use and mobile phone use, other than calling, having the longest use times. As far-field exposure was assumed to be continuous throughout the day, the duration of exposure was set to 1440 minutes (i.e., one day) (Table 5.3, Supplementary Materials). In addition to the duration of use of devices in general, the use of device functions was asked for tablets and mobile phones. This varied between age categories. Table 5.2 shows the percentage of participants using a specific function on their device, overall and stratified per age group. For mobile phones making phone calls, sending SMS messages and browsing the internet were the predominant uses. Tablets were used most often for browsing the internet and sending e-mails.

Table 5.2: Use of different mobile phone and tablet functions per age category.

Mobile phone functions	Overall	18-29	30-39	40-49	50-59	60-69	70+
N participants	*1755*	*180*	*208*	*245*	*316*	*425*	*220*
Phone calls	93%	97%	99%	96%	93%	89%	85%
Internet voice calls	46%	61%	63%	54%	48%	34%	24%
Internet video calls	21%	32%	34%	28%	20%	12%	5%
Sending SMS	82%	70%	71%	83%	88%	89%	78%
Sending voice messages	44%	69%	62%	51%	43%	29%	23%
Sending video messages	10%	27%	13%	8%	8%	5%	4%
Sending email	63%	90%	88%	76%	64%	48%	28%
Internet browsing	70%	95%	93%	83%	72%	55%	37%
Uploading videos/pictures	38%	68%	59%	52%	32%	23%	13%
Streaming music	25%	52%	40%	31%	21%	12%	5%
Streaming video	27%	63%	55%	35%	17%	8%	7%
Online games	15%	26%	26%	24%	13%	7%	5%
Mobile hotspot	20%	31%	29%	27%	20%	13%	7%
Tablet functions	**Overall**	**18-29**	**30-39**	**40-49**	**50-59**	**60-69**	**70+**
N participants	*1755*	*180*	*208*	*245*	*316*	*425*	*220*
Internet voice calls	13%	11%	9%	10%	14%	15%	14%
Internet video calls	20%	27%	26%	19%	19%	21%	14%
Sending SMS	7%	5%	5%	5%	5%	10%	11%
Sending voice messages	4%	2%	4%	3%	7%	3%	4%
Sending video messages	2%	1%	2%	2%	3%	1%	0%
Sending email	64%	66%	62%	60%	66%	68%	61%
Internet browsing	92%	93%	93%	95%	91%	92%	85%
Uploading videos/pictures	31%	29%	31%	29%	32%	32%	33%
Streaming music	23%	36%	30%	30%	18%	18%	11%
Streaming video	37%	63%	63%	46%	30%	24%	16%
Online games	26%	31%	34%	29%	22%	20%	30%

IEM results

Integrated dose

The median whole-body and whole-brain doses were 183.7 (p5-p95: 80.1 – 867.3) mJ/kg/day and 204.4 (p5-p95: 85.0 – 3323.7) mJ/kg/day respectively. For whole-body exposure far field of telecommunications and multiple other sources played a prominent role, while for the whole-brain the near-field sources were dominant. In both instances the near-to-far-field exposure to WiFi-routers was the third of the three main categories (i.e: near, near-to-far, far-field). Variation in doses was largest for near-field sources: while every participant has at least some exposure from near-field sources, the type of source contributing varies strongly as can be seen by the low median values per source. Table 5.3 shows the estimated doses for both tissues per source.

Table 5.3: Absolute dose in (mJ/kg/day) for whole-body and whole-brain.

	Whole-body (mJ/kg/day)				Whole-brain (mJ/kg/day)			
Source	P_5	Median	P_{95}	Mean	P_5	Median	P_{95}	Mean
Overall	**80.1**	**183.7**	**867.3**	**290.4**	**85.0**	**204.4**	**3323.7**	**810.5**
Near-field total	5.3	98.7	756.0	199.3	5.1	105.1	3235.1	719.6
Phone near head, 2G	0.0	5.3	236.8	49.0	0.0	70.4	3168.7	656.1
Phone near head, 3G	0.0	0.1	3.9	0.8	0.0	1.2	51.9	10.7
DECT phone near head	0.0	0.3	2.4	0.9	0.0	4.5	31.9	11.9
Phone with hands-free kit	0.0	0.0	343.0	37.9	0.0	0.0	1.5	0.2
Phone data	0.0	4.1	224.5	46.5	0.0	2.2	112.4	23.9
Tablet	0.0	0.2	212.8	42.6	0.0	0.0	59.3	13.3
Laptop	0.0	4.9	77.8	20.5	0.0	0.6	10.1	2.2
Body Area Network	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1
Smartwatch	0.0	0.0	2.9	0.5	0.0	0.0	0.0	0.0
Virtual reality headset	0.0	0.0	0.0	0.4	0.0	0.0	0.0	1.2
Near-to-far-field total	28.3	28.3	28.3	28.3	13.6	13.6	13.6	13.6
WiFi-router	28.3	28.3	28.3	28.3	13.6	13.6	13.6	13.6
Far-field total	29.6	56.6	124.0	62.8	36.1	68.4	121.8	77.3
Downlink	8.3	24.1	42.2	24.1	11.3	37.1	52.9	33.1
Uplink	10.1	15.7	23.3	15.9	15.3	22.6	29.6	21.6
Broadcast	4.9	12.0	53.6	19.2	2.6	7.7	16.8	8.2
DECT	0.5	1.3	4.3	1.9	0.6	5.1	34.0	13.0
WiFi	1.0	1.9	2.5	1.7	0.7	1.4	1.8	1.3

Country, age, and sex specific differences

The total dose for both the whole-body and whole-brain differed between countries, with Spanish participants having the highest estimated dose for both: nearly double of the overall median result. This appears to be driven by both higher near-field (1.5x for whole-body, 2x for whole-brain) and far-field exposure (respectively 1.6x and 1.7x higher compared to other countries). Conversely, French participants received doses well below the overall median. This could be an effect of the different age distributions between countries, with Spanish participants being younger on average and French participants being older on average (Supplementary Materials, Figure S5.6). Stratified by age, the highest median doses were seen for participants between 30-39 years old. In the higher age categories, the median dose was lower. No significant difference was observed between male and female participants (Table 5.4).

Table 5.4: Median dose (mJ/kg/day) and interquartile range (IQR) per source group, stratified for age, sex, and country

			Whole-body (mJ/kg/day) *Median (IQR)*		
	N	Near-field	Near-to-far-field	Far-field	Total
Overall	1755	98.7 (23, 211.1)	28.3 (28.3, 28.3)	56.6 (46.8, 67.7)	183.7 (105.8, 313.8)
Country					
France	478	27.4 (8.1, 116)	28.3 (28.3, 28.3)	59.7 (57.3, 67.7)	121.2 (100.6, 207.5)
Netherlands	568	106.9 (27.3, 251.5)	28.3 (28.3, 28.3)	50.3 (47.3, 56.6)	188.1 (108.3, 334.4)
Spain	321	152.9 (57.7, 351.8)	28.3 (28.3, 28.3)	119.5 (105.5, 124.4)	302.1 (208.6, 502.8)
Switzerland	388	99.4 (24.8, 197.9)	28.3 (28.3, 28.3)	33.5 (29.9, 35.7)	161.1 (82.9, 260.9)
Age					
18-29 years	180	177.4 (83.1, 425.4)	28.3 (28.3, 28.3)	61.7 (38, 129.2)	294.6 (191.1, 516.7)
30-39 years	208	176.3 (100, 422.9)	28.3 (28.3, 28.3)	59.9 (49.4, 123.5)	295.8 (189, 545.1)
40-49 years	245	126.8 (36.2, 300.6)	28.3 (28.3, 28.3)	56.9 (47.9, 101.3)	223.5 (139.5, 402.2)
50-59 years	316	86 (21.3, 179.3)	28.3 (28.3, 28.3)	55.6 (36.4, 59.1)	168.2 (103.4, 266.6)
60-69 years	425	39.3 (11.1, 126.2)	28.3 (28.3, 28.3)	56.4 (46.5, 65.2)	131.1 (97.6, 209)
70+ years	220	24.8 (6.9, 97.1)	28.3 (28.3, 28.3)	56.4 (48.5, 59.2)	108.9 (90.6, 181.3)
Sex					
Male	892	95.5 (19.6, 183.8)	28.3 (28.3, 28.3)	49.3 (46.5, 57.3)	171.8 (97.8, 265.8)
Female	863	104.5 (25.9, 255.2)	28.3 (28.3, 28.3)	63.7 (55.6, 75)	197.3 (117.5, 357.8)
			Whole-brain (mJ/kg/day) *Median (IQR)*		
	N	Near-field	Near-to-far-field	Far-field	Total
Overall	1755	105.1 (75.4, 1298.8)	13.6 (13.6, 13.6)	68.4 (63.5, 94.7)	204.4 (150.5, 1377.5)
Country					
France	478	76.9 (16.2, 1290.1)	13.6 (13.6, 13.6)	68.6 (64.9, 76.1)	159.5 (108.8, 1369.4)
Netherlands	568	113.9 (76.6, 1300.8)	13.6 (13.6, 13.6)	67.3 (63.5, 69.8)	205 (156.9, 1381.9)
Spain	321	207.3 (90, 1319.8)	13.6 (13.6, 13.6)	103.3 (101.1, 108.5)	350.4 (210.4, 1440.5)
Switzerland	388	107.6 (77.1, 1300.4)	13.6 (13.6, 13.6)	39.9 (38.9, 50.9)	186 (130.6, 1354.6)
Age					
18-29 years	180	207.6 (91.5, 1311.3)	13.6 (13.6, 13.6)	69.8 (43.4, 103.3)	301.3 (187.6, 1415.8)
30-39 years	208	288.7 (104.9, 1325)	13.6 (13.6, 13.6)	74.7 (64.2, 103.5)	431.3 (207.2, 1433.8)
40-49 years	245	162.7 (79.9, 1319.7)	13.6 (13.6, 13.6)	69.8 (64.2, 101.1)	270.8 (158, 1420.4)
50-59 years	316	91.5 (73.4, 1300.3)	13.6 (13.6, 13.6)	67.3 (62.8, 74.7)	185.5 (136.7, 1380.9)
60-69 years	425	83.5 (72.7, 1290.3)	13.6 (13.6, 13.6)	67.3 (63.5, 74.7)	165.3 (147.5, 1364.7)
70+ years	220	77.4 (71.6, 130.5)	13.6 (13.6, 13.6)	67.3 (64.2, 69.3)	158.5 (133.5, 233.5)
Sex					
Male	892	91.4 (73.1, 1295.5)	13.6 (13.6, 13.6)	64.9 (62.8, 74.7)	183.9 (148, 1372.8)
Female	863	120 (77.9, 1301.7)	13.6 (13.6, 13.6)	70.8 (65.3, 103.3)	224.3 (156.1, 1384.3)

Relative contribution of sources

The distribution of RF source contributions clearly differed between whole-body and whole-brain dose (Figure 5.2). Whole-brain dose was dominated by mobile phone use at 2G networks, followed by nearby WiFi networks. Mobile phone calls were less relevant for whole-body exposure however: WiFi-routers, laptops, tablets, and other phone use contributed more. A log scaled version of results shown in Figure 5.2 is provided to be able to distinguish sources providing lower levels of contribution (Figure S5.1, Supplementary Materials). The relative contributions for the other anatomical sites can be found in Figure S5.8 (Supplementary Materials) in the form of a heat map.

Contribution of specific functions

Mobile phone calls were the dominating contributor to whole-brain dose, with only marginal contributions from other functions. For whole-body dose browsing, uploading data, and streaming videos are present as well (Figure 5.3). Looking at the relative contribution of tablet functions, little difference was observed between whole-body and whole-brain. Browsing the internet and streaming videos are the most relevant functions for tablet use (Figure 5.4), while calls dominate mobile phone use (Figure 5.3). In addition, Figure 5.3 and Figure 5.4 can be viewed on a log scale as Figure S5.2 and Figure S5.3 (Supplementary Materials) for more details on the other functions.

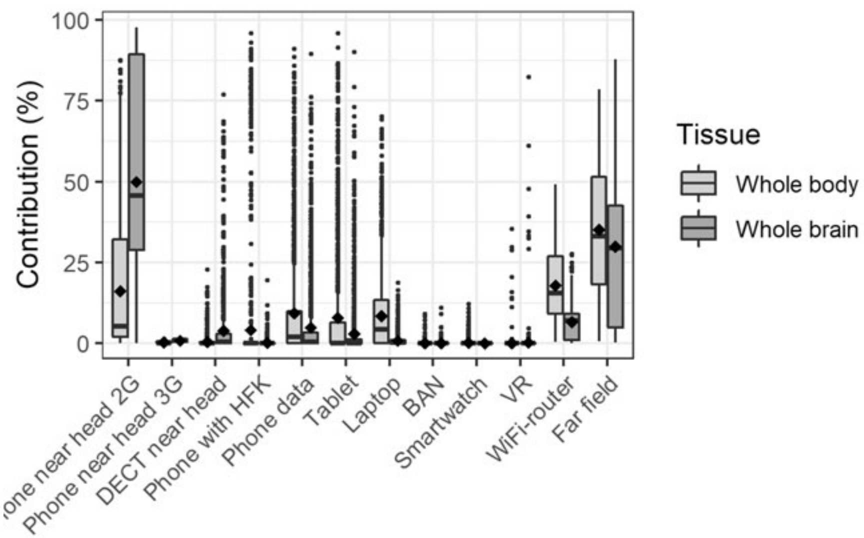

Figure 5.2: Relative contribution of sources to total dose of whole-body and whole-brain (HFK: hands-free kit, BAN: Body Area Network, VR: Virtual Reality headset). Percentile distribution is shown using boxplots and means are indicated with a diamond marker.

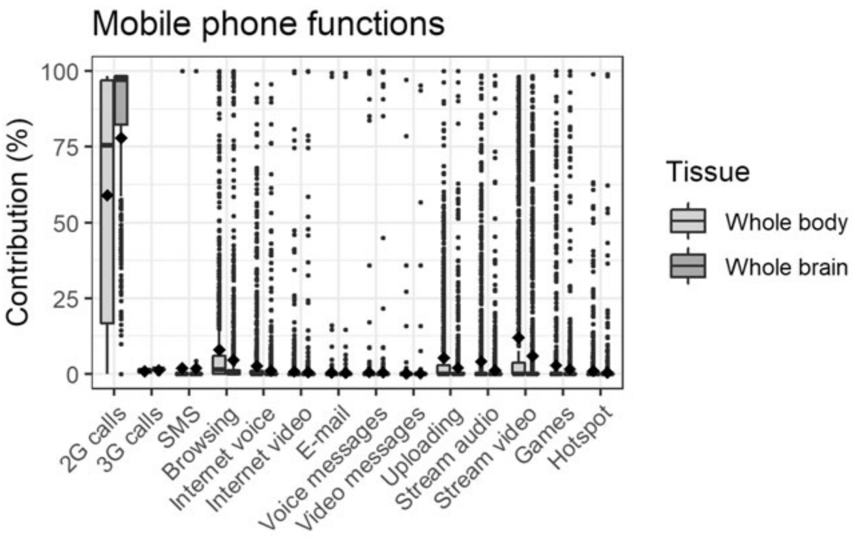

Figure 5.3: Relative contribution of mobile phone functions to total dose of whole-body and whole-brain. Percentile distribution is shown using box-whiskerplots and means are indicated with a diamond marker.

Sensitivity analyses

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Two sensitivity analyses were performed by modifying the WiFi-router exposure duration. Total dose from WiFi-router exposure is reduced by 50% and raised to 200% when respectively lowering by half or doubling the estimated time spent within the presence of an active WiFi-router. For relative contributions, halving the dose brings the dose contribution on the same level as far-field exposure. The full details can be found in the Supplementary Materials (Tables S5.4 and S5.5; Figures S5.4 and S5.5).

Discussion

We designed the most comprehensive RF-EMF dose estimation tool to date, capable of estimating RF-EMF dose from near-field, near-to-far-field, and far-field sources for up to 64 anatomical sites. We applied this Integrated Exposure Model to an international survey on mobile device use in four European countries in order to obtain population RF-EMF exposure profiles. The median dose was found to be 183.7 (p5-p95: 80.1 – 867.3) mJ/kg/day and 204.4 (p5-p95: 85.0

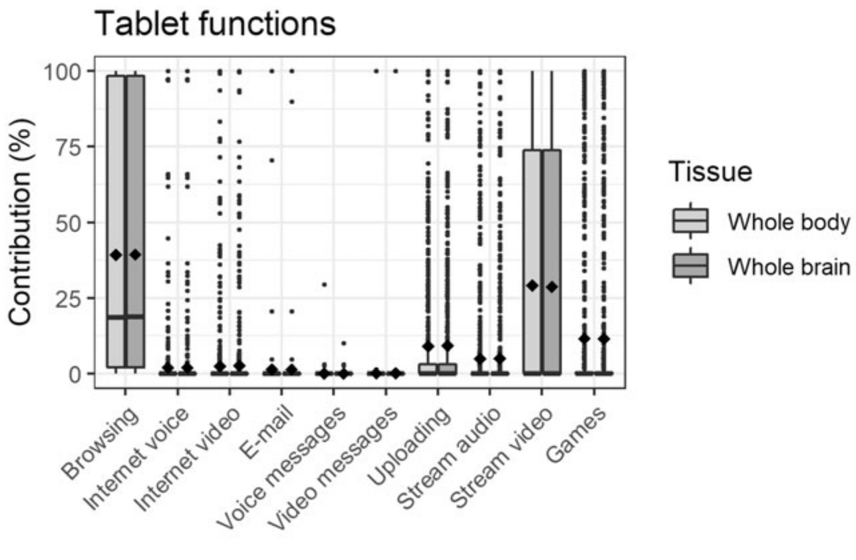

Figure 5.4: Relative contribution of tablet functions to total dose of whole-body and whole-brain. Percentile distribution is shown using boxplots and means are indicated with a diamond marker.

– 3323.7) mJ/kg/day for whole-body and whole-brain respectively. The median dose varied per country and per age group, with overall doses found to be higher in younger age groups for both the whole-body and the whole-brain. Notable differences were seen between Spanish (higher) and French (lower) participants. Near-field and far-field doses are driving these differences. As French participants used near-field devices for shorter amounts of time on average, their resulting near-field RF-EMF dose was lower. When looking at the 30-39 years group (i.e.: with the highest total dose) this effect held true but was less pronounced with a median near-field dose of 132.8 (France) versus 189.3 (Spain). The lower use time can be partly related to the higher average age of this group, as well as cultural differences. The higher far-field dose in Spanish participants can be traced back to higher exposure levels measured in the Spanish part of the GERoNiMO data used, in particular on the FM radio frequency bands (Table 5.1). Looking at the relative contribution of sources, mobile phone calls near the head were the main contributor for whole-brain dose followed by far-field sources and a smaller contribution of nearby WiFi-routers. For the whole-body dose contributions, on the other hand, far-field telecommunication sources together with other sources (WiFi-routers (in the near-to-far-field), laptops, tablets, and other mobile phone functions than calls) provided higher contributions. For other anatomical sites the dose is driven by relative contributions from phone and tablet data use, far-field sources and WiFi-routers. This illustrates the importance of taking multiple RF-EMF sources into account when looking at anatomical sites other than the brain, for instance potential health endpoints in organs such as the heart, liver, or pancreas related to devices held in different positions around or on the body.

Strengths and limitations

Main strengths of our model include the large number of RF-EMF sources and anatomical sites included: both nearby and further away sources can be assessed, and dose estimates are available for many anatomical sites besides the whole-brain and specific brain regions. The ability to include as many device use functions as desired with accompanying output powers and use durations allows for detailed dose estimations: rather than a single whole day average, many use cases and situations can be included. Detailed input information has to be available however, either from interviews, questionnaires, or monitoring apps concerning mobile device use. Novel devices and use functions are continuously being developed, requiring regular updates to dose estimation models. The modular structure of our model allows for integration of information on new sources and uses as those become available. For example, while the current WiFi-router module is based on the 2450MHz frequency, the module can be updated to include 5GHz networks. Limitations include the number of assumptions needed in dose modelling: the current version is for the most part limited to 2450MHz transmissions. As the SAR is dependent on the frequency, different frequencies will result in different dose estimations. The three main factors in dose estimation, SAR, output power, and duration of use, each introduced uncertainties in the model, leading to a large global uncertainty on an individual level. For SAR estimations uncertainty in both model input parameters and interpolation methods used will propagate through the transfer (8). Estimating the output power proved to be difficult. The total dose strongly depends on the output power strength of the source, and output power is dependent on many factors including current use and reception quality. Little information on output power is available in existing literature, therefore we had to depend largely on expert opinions. For duration of use, proxy data and assumptions were included when there was no survey data available. Concerning the survey, the response rate was relatively low: 1755 responses (4.4%) out of 40,000 invitations limiting generalisability of the results. There were differences in the age distribution between the four participating countries, with the participants from France being the oldest and Spain having mostly younger participants. The age differences may have influenced the difference between countries, with Spain having both the youngest group of participants and the highest median doses together with higher far-field exposure information for Spanish participants. Despite these drawbacks, the survey is the most detailed source of information available on the use of modern communication devices to date and included a large number of participants.

Dose estimations

Two previous publications (7,22) described a similar dose integration model for estimating RF-EMF dose. The model of Roser *et al.* includes near-field sources in the form of mobile and DECT phones, laptops and tablets, as well as far-field sources. The mean whole-body (339.9 mJ/kg/day) and mean whole-brain (1559.7 mJ/kg/day) doses found by Roser *et al.* were higher than our mean findings (290.4 and 801.5 mJ/kg/day respectively). The main difference between mean whole-brain doses is driven by higher near-field dose in Roser *et al.*, in particular from GSM900/GSM1800 mobile phone calls made near the head. This could be explained by the fact that we found an average duration of nearly ten minutes for 2G and 3G phone calls combined versus the 17.2 minutes used by Roser *et al.* While not specified, different assumptions on network technology used (i.e., 2G versus 3G) could further influence estimations, as 3G technology uses lower output powers. Conversely, our far-field estimations were higher which can be traced back to the input data concerning far-field exposure: the time-weighted average exposures from the GERoNiMO measurements was higher than those used by Roser *et al.*, which could be explained by increasing use of RF-EMF in society over the years, with the GERoNiMO measurements being more recent (September 2014 – February 2016 versus June 2012 – March 2013). Comparing our results to the model of Lauer *et al.*, the estimated far-field dose is very similar, with Lauer *et al.* defining three exposed groups (residency nearby a broadcast transmitter, self-selected volunteers, residency close to a mobile phone base station) with far-field dose results ranging from 35.2 – 73.5 mJ/kg/day for the whole-body, while we observed a median dose of 56.4 mJ/kg/day. The advantages of our model over these previous models are the ability to: include multiple use cases each with their own related output power and position relative to the body (i.e., the scenarios of use); to include new technologies, devices and uses as they are deployed; and to estimate dose for many more anatomical sites.

Relative contributions per source

For the whole-brain the use of mobile phones near the head remains by far the main contributor to total dose. In particular phone calls performed on a 2G network, which generally uses a higher output power, provide a high contribution followed at a distance by nearby WiFi-routers. Regarding whole-body dose, the contribution of other sources becomes more important. Far-field exposure, WiFi-routers, laptops, tablets, and even other functions than calling on a mobile phone provide a higher contribution to the whole-body dose. This indicates that while just looking at mobile phone calls may include most RF-EMF exposure for health outcomes focused on the brain, this is not the case for the whole-body. In addition, adaptive output power control depending on the mobile phones' function may further influence exposure levels, as explained below. When looking at potential health endpoints at anatomical sites other than the brain (e.g., heart, liver), these devices should be included.

Mobile phone and tablet functions

With the wealth of information available from the CREST Mobile Phone Use Survey, we were able to distinguish between many different use of mobile phones and tablets. For mobile phones, 2G phone calls are the main contributing usage to RF-EMF dose. However, calls over 2G networks are becoming less common, with 3G, 4G, and in the future 5G being used instead. Should 2G call duration reduce, other uses such as browsing and streaming become more prominent. For tablets, where no calls on 2G or 3G networks were performed, browsing and streaming video are already main contributors to total dose for both the whole-brain and whole-body dose. Identifying the main uses and functions contributing to RF-EMF dose of different anatomical sites aids in designing new epidemiological studies, with questions concentrating on the most prominent uses, and aids in the development of risk intervention tools by focusing specifically on the main dose contributors.

RF-EMF dose reduction

With the relative contributions found in this study, various non-technical interventions may be considered to reduce overall RF-EMF dose. In particular the avoidance of using a mobile phone near the head when using 2G networks may be an efficient way to reduce overall exposure by half for the whole-brain and up to 25% for the whole-body. This can be achieved on modern smartphones by disabling the use of 2G networks altogether or by using a wired hands-free kit instead. In the latter case, the exposure will shift from the head to other parts of the body when the device is held in a hand or pocket. Additionally, speech intelligibility might suffer from such measures, potentially increasing the phone calls and thus the dose (23). In general, we observed a higher RF-EMF dose with device functions that require higher amounts of data, such as video streaming. Placing the device on a nearby surface or stand with data intensive uses can be considered to reduce dose. For far-field exposure it is generally difficult to achieve individual reduction as these are continuous exposures generally not controlled by the subject, such as FM radio broadcast and mobile phone antennas.

Conclusion

In conclusion, we developed the most comprehensive RF-EMF dose estimation tools to date. Realistic population exposure scenarios were obtained by using data on mobile phone use from an international survey in the model. Overall RF-EMF dose for the whole-body and whole-brain was found to be higher in younger age groups in comparison with older groups. Differences between included countries were observed, driven by both differing use profiles and differing far-field exposures. Mobile phone calls on 2G networks were found to be the main contributor to whole-brain RF-EMF dose. For whole-body dose, far-field of telecommunications and multiple other RF-EMF sources played a prominent role as well. These findings can be used in the creation of non-technical interventions aimed at lowering RF-EMF exposure from current technologies, with the modular structure of the model allowing inclusion of new technologies such as 5th generation networks. Future epidemiological studies involving RF-EMF exposure should take multiple RF-EMF sources into account by adding detailed questions on exposure duration (i.e., position and function usage) when investigating other anatomical sites than the brain.

Acknowledgements

Declaration of interest

All authors declare that they have no conflicts of interest

Grant sponsors

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Supplementary Materials

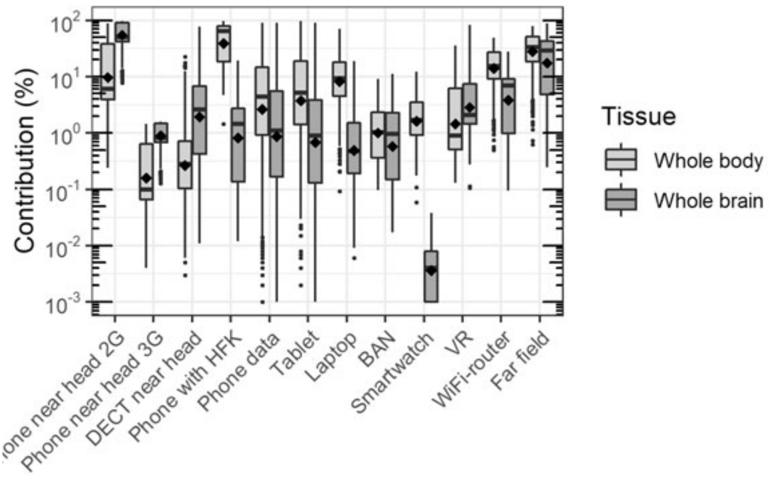

Figure S5.1: Relative contribution of sources to total dose of whole-body and whole-brain, log scale.

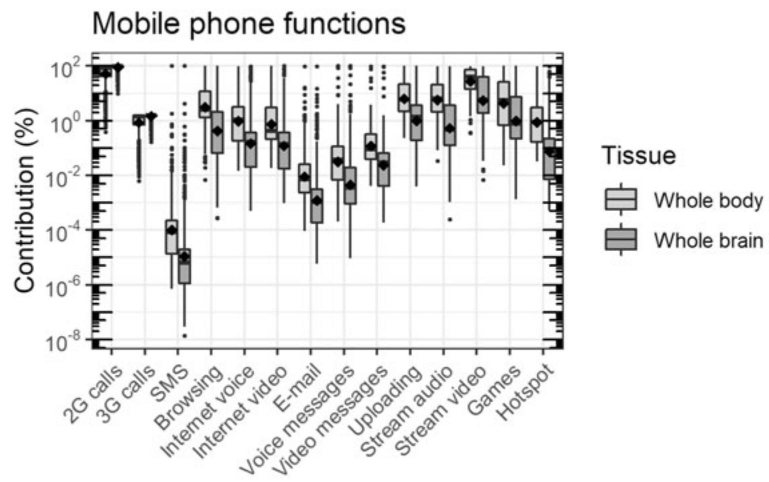

Figure S5.2: Relative contribution of mobile phone functions to total dose of whole-body and whole-brain, log scale.

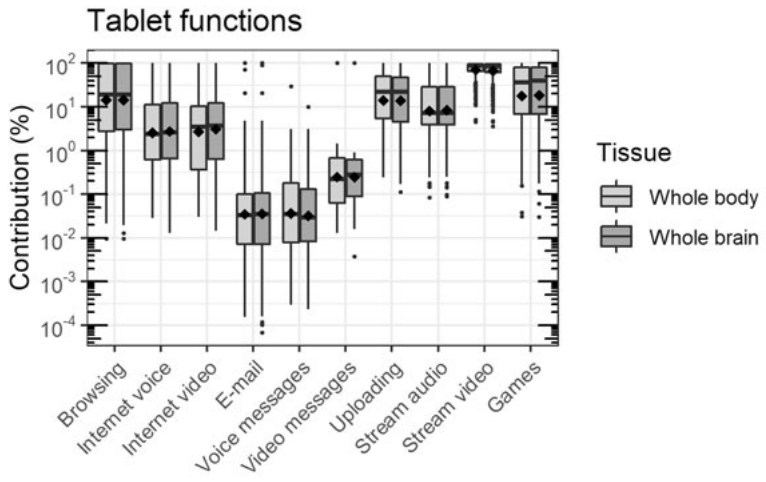

Figure S5.3: Relative contribution of tablet functions to total dose of whole-body and whole-brain, log scale.

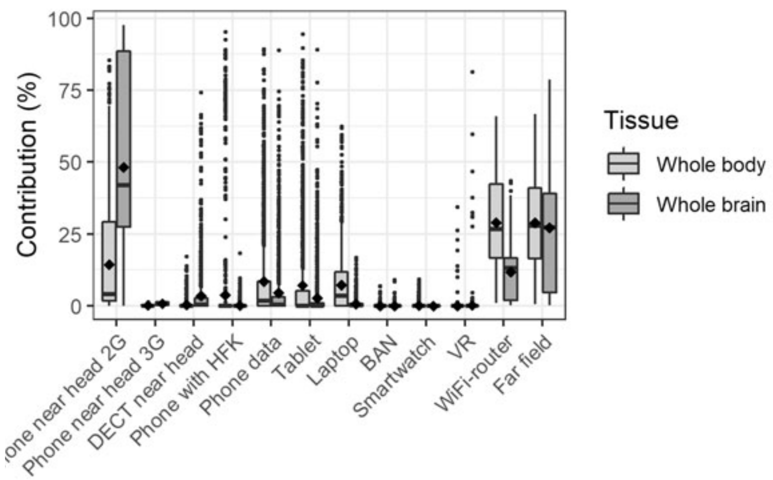

Figure S5.4: Relative contribution of sources to total dose of whole-body and whole-brain (2h WiFi).

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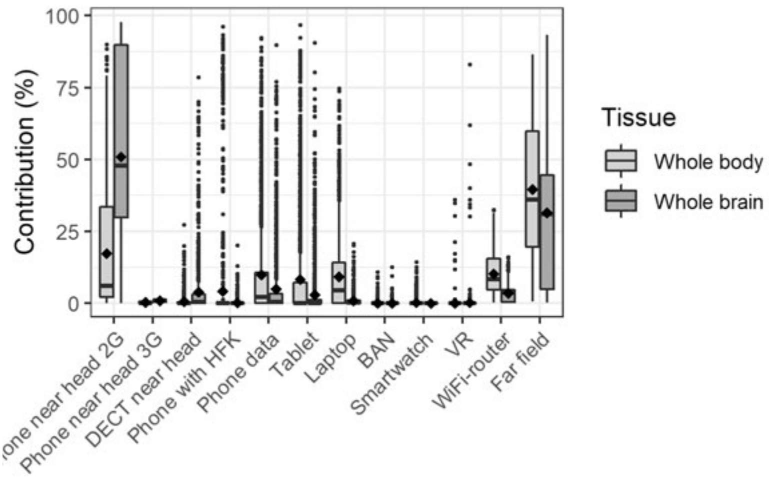

Figure S5.5: Relative contribution of sources to total dose of whole-body and whole-brain (0.5h WiFi).

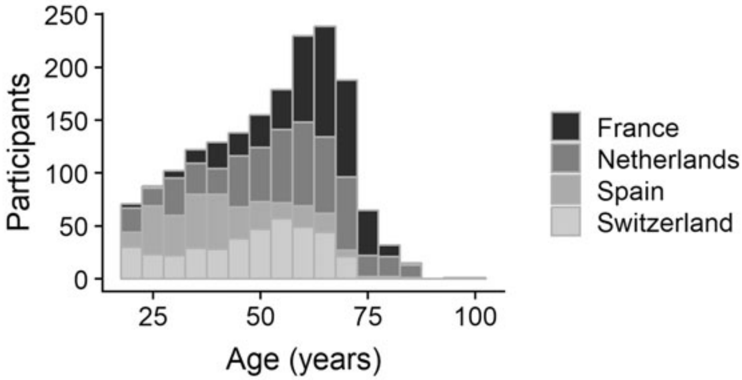

Figure S5.6: Age distribution over four countries.

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#	Tissue	BAN	Mobile, DECT near head	Laptop	On or near body, phone headset	Smartwatch	Tablet data, phone data	Virtual reality	WiFi-router	Far-field
1	Adrenal gland	X			X	X	X			
2	Anterior brain								X	X
3	Artery	X			X	X	X			
4	Bladder	X			X	X	X			
5	Bones	X			X	X	X			
6	Brain left		X						X	X
7	Brain right		X						X	X
8	Brainstem left						X	X		
9	Brainstem right						X	X		
10	Bronchus	X			X	X	X			
11	Cartilage	X			X	X	X			
12	Cerebellum	X	X		X	X	X	X		
13	Cerebrospinal fluid	X			X	X	X			
14	Corpus callosum	X			X	X	X			
15	Diaphragm	X			X	X	X			
16	Dura mater	X			X	X	X			
17	Esophagus	X			X	X	X			
18	Eye	X			X	X	X			
19	Fat	X			X	X	X			
20	Frontal left		X				X	X	X	X
21	Frontal right		X				X	X	X	X
22	Gallbladder	X			X	X	X			
23	Heart	X			X	X	X			
24	Hippocampus	X			X	X	X			
25	Kidney	X			X	X	X			
26	Large intestine	X			X	X	X			
27	Larynx	X			X	X	X			
28	Limbic left brain						X	X	X	X
29	Limbic right brain						X	X	X	X
30	Liver	X			X	X	X			
31	Lung	X			X	X	X			
32	Lymph node	X			X	X	X			
33	Medulla oblongata	X	X		X	X	X		X	X
34	Midbrain	X	X		X	X	X		X	X
35	Mucosa	X			X	X	X			
36	Muscle	X			X	X	X			
37	Nerve	X			X	X	X			
38	Occipital left brain		X				X	X	X	X
39	Occipital right brain		X				X	X	X	X
40	Pancreas	X			X	X	X			
41	Parietal left brain		X				X	X	X	X
42	Parietal right brain		X				X	X	X	X
43	Pineal body	X			X	X	X			
44	Pons	X	X		X	X	X		X	X
45	Posterior brain								X	X
46	Salivary gland	X			X	X	X			
47	SAT	X			X	X	X			
48	Skin	X			X	X	X			
49	Small intestine	X			X	X	X			
50	Spinal cord	X			X	X	X			
51	Spleen	X			X	X	X			
52	Stomach	X			X	X	X			
53	Sub-lobar left brain						X	X	X	X
54	Sub-lobar right brain						X	X	X	X
55	Temporal left brain		X				X	X	X	X
56	Temporal right brain		X				X	X	X	X
57	Thalamus	X			X	X	X			
58	Thyroid gland	X			X	X	X			
59	Tongue	X			X	X	X			
60	Trachea	X			X	X	X			
61	Urethra	X			X	X	X			
62	Vein	X			X	X	X			
63	Whole-body	X	X	X	X	X	X	X	X	X
64	Whole-brain	X	X	X	X	X	X	X	X	X

Figure S5.7: In-body anatomical sites included (shown by [X]) in the model, listed per source.

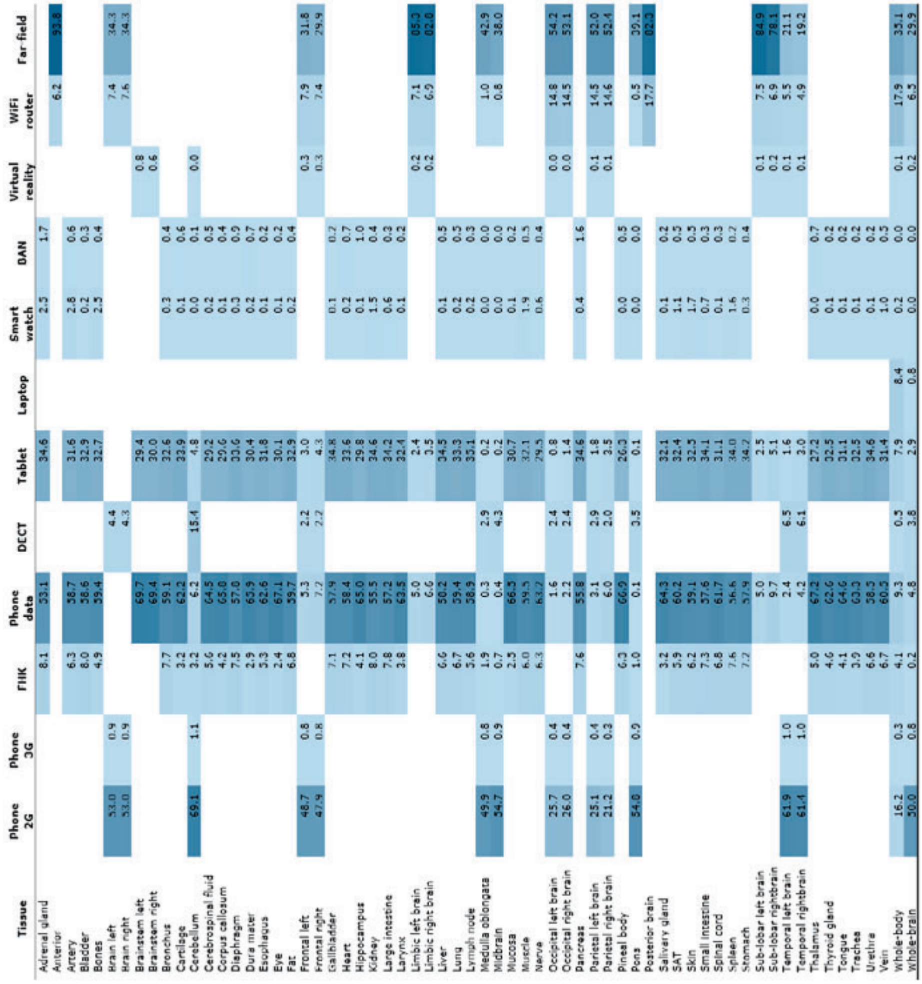


Figure S5.8: Heat map of all included anatomical sites. Numbers represent the mean relative contribution to total dose for each specific site.

Table S5.1: Use positions included in the model.

Source	Position
Mobile phone	Near the head
	Hands-free kit (i.e., device on/near body)
	Averaged position data (i.e., averaged over the specific positions below)
	a. 20 cm in front of eyes
	b. 30 cm in front of eyes
	c. 20 cm in front of stomach
	d, 30 cm in front of stomach
	e. In front of stomach, horizontal (i.e.: laid flat)
	f. On a surface in front of body
	g. In front of body, above legs
DECT phone	Near the head
Body Area Network	Averaged position (i.e., averaged over the specific positions below)
	a. 20 cm in front of eyes
	b. 30 cm in front of eyes
	c. 20 cm in front of stomach
Tablet	Averaged position (i.e., averaged over the specific positions below)
	a. 20 cm in front of eyes
	b. 30 cm in front of eyes
	c. 20 cm in front of stomach
	d, 30 cm in front of stomach
	e. In front of stomach, horizontal (i.e.: laid flat)
	f. On a surface in front of body
	g. In front of body, above legs
Laptop	Averaged position
On/near body device	Averaged position
Smartwatch	Wrist
Virtual Reality glasses	In front of eyes
WiFi-router	Averaged over multiple points in a 13mx13m room
Far-field	*Not applicable*

Table S5.2: Proxy data used for personal parameters.

Age (years)	Mass (kg)							
	Male				Female			
	FR	NL	ES	CH	FR	NL	ES	CH
<20	65.3	79.8	65.8	73.3	65.3	67.1	65.8	60.3
20-24	65.3	79.8	65.8	73.3	65.3	67.1	65.8	60.3
25-29	68.2	79.8	70.2	79.4	68.2	67.1	70.2	62.4
30-34	68.2	84.6	70.2	79.4	68.2	69.9	70.2	62.4
35-39	68.2	84.6	70.2	81.3	68.2	69.9	70.2	63.9
40-44	72.2	87.8	72.1	81.3	72.2	73.1	72.1	63.9
45-49	72.2	87.8	72.1	82.3	72.2	73.1	72.1	65.3
50-54	72.2	87.2	72.1	82.3	72.2	73.5	72.1	65.3
55-59	71	87.2	72.3	82.1	71	72.4	72.3	67.0
60-64	71	87.2	72.3	82.1	71	72.4	72.3	67.0
65-69	71	85.5	72.3	81.0	71	73	72.3	67.4
70-74	71	85.5	72.3	81.0	71	73	72.3	67.4
>75	71	80	72.3	76.5	71	69.9	72.3	65.3
Age (years)	**Height (cm)**							
	Male				Female			
	FR	NL	ES	CH	FR	NL	ES	CH
<20	171.3	183.4	171.2	178.5	171.3	168.6	171.2	166.1
20-24	171.3	183.4	171.2	178.5	171.3	168.6	171.2	166.1
25-29	170.3	183.4	169	178.9	170.3	168.6	169	166.3
30-34	170.3	182.7	169	178.9	170.3	168.4	169	166.3
35-39	170.3	182.7	169	178.3	170.3	167.7	169	165.5
40-44	169.3	182.6	167.4	178.3	169.3	167.1	167.4	165.5
45-49	169.3	182.6	167.4	177.1	169.3	164.9	167.4	165.2
50-54	169.3	181.6	167.4	177.1	169.3	168.3	167.4	165.2
55-59	165.6	180.5	162.9	175.8	165.6	166.6	162.9	163.8
60-64	165.6	180.5	162.9	175.8	165.6	166.6	162.9	163.8
65-69	165.6	178.3	162.9	174.3	165.6	165.7	162.9	163.0
70-74	165.6	178.3	162.9	174.3	165.6	165.7	162.9	163.0
>75	165.6	175.7	162.9	172.3	165.6	162.2	162.9	161.2

France (FR): Special Eurobarometer 246 (15)
Netherlands (NL): Statistics Netherlands (CBS) (13)
Spain (ES): Special Eurobarometer 246 (15)
Switzerland (CH): Swiss Gesundheidsbefragung 2012 (14)

Table S5.3: Durations of use for different sources per day, in minutes.

Source	P5	Median	P95	Mean
Near-field				
Phone near head, 2G	0	0.6	24.8	5.1
Phone near head, 3G	0	0.5	20.3	4.2
DECT phone near head[a]	0	2.4	17.1	6.4
Phone headset	0	0	18	1.7
Phone data	0	19.1	218.6	47.0
Tablet	0	1.0	137.9	29.6
Laptop	0	30	480	126.6
Body Area Network	0	0	0	4.1
Smartwatch	0	0	120	22.0
Virtual reality headset	0	0	0	0.2
Near-to-far-field				
WiFi-router	60	60	60	60
Far-field				
Far-field[b]	1440	1440	1440	1440

[a] DECT phone information from the AMIGO study (11)
[b] Exposure to far-field was assumed to be constant throughout the day, resulting in 1440 minutes (i.e. one day)

Table S5.4: Sensitivity analysis: Absolute dose in (mJ/kg/day) for whole-body and whole-brain, 2 hour WiFi-router.

	Whole-body (mJ/kg/day)				Whole-brain (mJ/kg/day)			
Source	P_5	Median	P_{95}	Mean	P_5	Median	P_{95}	Mean
Overall	**108.3**	**212.0**	**895.6**	**318.6**	**98.6**	**218.0**	**3337.3**	**824.1**
Near-field total	5.3	98.7	756.0	199.3	5.1	105.1	3235.1	719.6
Phone near head, 2G	0.0	5.3	236.8	49.0	0.0	70.4	3168.7	656.1
Phone near head, 3G	0.0	0.1	3.9	0.8	0.0	1.2	51.9	10.7
DECT phone near head	0.0	0.3	2.4	0.9	0.0	4.5	31.9	11.9
Phone with hands-free kit	0.0	0.0	343.0	37.9	0.0	0.0	1.5	0.2
Phone data	0.0	4.1	224.5	46.5	0.0	2.2	112.4	23.9
Tablet	0.0	0.2	212.8	42.6	0.0	0.0	59.3	13.3
Laptop	0.0	4.9	77.8	20.5	0.0	0.6	10.1	2.2
Body Area Network	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1
Smartwatch	0.0	0.0	2.9	0.5	0.0	0.0	0.0	0.0
Virtual reality headset	0.0	0.0	0.0	0.4	0.0	0.0	0.0	1.2
Near-to-far-field total	56.5	56.5	56.5	56.5	27.2	27.2	27.2	27.2
WiFi-router	56.5	56.5	56.5	56.5	27.2	27.2	27.2	27.2
Far-field total	29.6	56.6	124.0	62.8	36.1	68.4	121.8	77.3
Downlink	8.3	24.1	42.2	24.1	11.3	37.1	52.9	33.1
Uplink	10.1	15.7	23.3	15.9	15.3	22.6	29.6	21.6
Broadcast	4.9	12.0	53.6	19.2	2.6	7.7	16.8	8.2
DECT	0.5	1.3	4.3	1.9	0.6	5.1	34.0	13.0
WiFi	1.0	1.9	2.5	1.7	0.7	1.4	1.8	1.3

Table S5.5: Sensitivity analysis: Absolute dose in (mJ/kg/day) for whole-body and whole-brain, 0.5 hour WiFi-router.

	Whole-body (mJ/kg/day)				Whole-brain (mJ/kg/day)			
Source	P_5	Median	P_{95}	Mean	P_5	Median	P_{95}	Mean
Overall	**66.0**	**169.6**	**853.2**	**276.2**	**78.3**	**197.6**	**3316.9**	**803.7**
Near-field total	5.3	98.7	756.0	199.3	5.1	105.1	3235.1	719.6
Phone near head, 2G	0.0	5.3	236.8	49.0	0.0	70.4	3168.7	656.1
Phone near head, 3G	0.0	0.1	3.9	0.8	0.0	1.2	51.9	10.7
DECT phone near head	0.0	0.3	2.4	0.9	0.0	4.5	31.9	11.9
Phone with hands-free kit	0.0	0.0	343.0	37.9	0.0	0.0	1.5	0.2
Phone data	0.0	4.1	224.5	46.5	0.0	2.2	112.4	23.9
Tablet	0.0	0.2	212.8	42.6	0.0	0.0	59.3	13.3
Laptop	0.0	4.9	77.8	20.5	0.0	0.6	10.1	2.2
Body Area Network	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1
Smartwatch	0.0	0.0	2.9	0.5	0.0	0.0	0.0	0.0
Virtual reality headset	0.0	0.0	0.0	0.4	0.0	0.0	0.0	1.2
Near-to-far-field total								
WiFi-router	14.1	14.1	14.1	14.1	6.8	6.8	6.8	6.8
Far-field total	14.1	14.1	14.1	14.1	6.8	6.8	6.8	6.8
Downlink								
Uplink	29.6	56.6	124.0	62.8	36.1	68.4	121.8	77.3
Broadcast	8.3	24.1	42.2	24.1	11.3	37.1	52.9	33.1
DECT	10.1	15.7	23.3	15.9	15.3	22.6	29.6	21.6
WiFi	4.9	12.0	53.6	19.2	2.6	7.7	16.8	8.2

Characterizing patterns of use of mobile communication technologies

Welcome! This questionnaire consists of five parts. It is anonymous and does save personal information. It will take approximately 20 minutes to complete the questionnaire.

In the 90s mobile communication technologies were mainly limited to the use of mobile phones used to make voice calls. People usually held their mobile phone close to the ear. Recent years have seen a rapid evolution with the introduction of numerous new devices, applications and technologies.

Phones, tablets, laptops and other devices are used to surf the internet, send messages, stream videos, etc. The introduction of these devices has been accompanied by the rapid development of new types of networks (WiFi, LTE) and network configurations to support their uses.

The CREST project is a European study which aims to identify new communicating devices, characterize new uses and identify new communication technologies that will support these devices in the coming years.

We have, at present, little information on usage patterns of these new devices and technologies in the general population. As such we are interested in gathering information on current patterns and trends. By completing this questionnaire you help us achieve this objective.

There are 38 questions in this survey

About you

[]What is your gender? *

Please choose only one of the following:

O Male

O Female

[]What is your age? *

Only numbers may be entered in this field.

Please write your answer here:

[]Are you right or left handed? *

Please choose **only one** of the following:

O Right handed

O Left handed

O Ambidextrous

[]What is the highest level of formal education you have completed? *

Please choose only one of the following:

O Primary school

O Secondary school

O Vocational education

O College

O University

O Postgraduate degree

5

[]Which one of the following best describes your current occupational situation?*

Please choose **only one** of the following:

- O Studying
- O Employed
- O Self-employed
- O Unemployed
- O Parental leave
- O Long-term sick leave / disability
- O Housewife / househusband
- O Retired
- O Other

[]Which one of the following best describes your current place of residence? *

Please choose **only one** of the following:

- O Village (up to 5000 residents)
- O Town or suburbs of a large city (5000 - 100 000 residents)
- O City (more than 100 000 residents)

[]Which of the following best describes your current place of employment or study? *

Only answer this question if the following conditions are met:

Answer was 'Employed' or 'Studying' or 'Self-employed' or 'Parental leave' at question '5 [Q1005]' (Which one of the following best describes your current occupational situation?)

Please choose **only one** of the following:

- O Village (up to 5000 residents)
- O Town or suburbs of a large city (5000 - 100 000 residents)
- O City (more than 100 000 residents)

[]How many of the following devices do you use on a regular basis? This includes devices for work and private use. *

Please write your answer(s) here:

Classic mobile phones (i.e. not a smartphone)

Smartphones

Tablets

Phablets (e.g Samsung Note, Pantech Pocket)

Laptops (including netbooks, ultrabooks)

WiFi enabled portable media players (e.g. iPod Touch)

E-readers (e.g. Kindle, Kobo)

Activity/life trackers (e.g. Jawbone, Fitbit)

Body-worn sensors (e.g. medical sensors)

Smart watches

Other mobile device (please specify below)

5

[]Please specify the "other mobile device" from the previous question: *

Only answer this question if the following conditions are met:

Answer was greater than '0' at question '8 [Q1008]' (How many of the following devices do you use on a regular basis? This includes devices for work and private use. (Other mobile device (please specify below)))

Please write your answer here:

Your use of mobile phones

The following questions address your use of **mobile phones**. This does not include tablets or phablets.

If you cannot recall, please make a qualified guess.

[]Did you use a **mobile phone** during the last three months? *

Please choose only one of the following:

- Yes
- No

[]How long have you used a mobile phone? *

Only answer this question if **the following conditions are met:**

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?) Please choose only one of the following:

- Less than 1 year
- 1 to 4 years
- 5 to 10 years
- More than 10 years

[]Where do you mainly **carry or store** your mobile phone when you are not using it..

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?)

Please choose the appropriate response for each item:

	In my hand	In a pocket or belt case (at or below waist level)	In a breast pocket	In my bra or fitted sports top	Hanging against my chest	Elsewhere on my body	In a bag, or elsewhere not in my clothing
At home	○	○	○	○	○	○	○
At work / school	○	○	○	○	○	○	○
In a vehicle	○	○	○	○	○	○	○
Elsewhere indoors	○	○	○	○	○	○	○
Outdoors	○	○	○	○	○	○	○

[]When you are **not using** your mobile phone, is it usually: *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?)

Please choose the appropriate response for each item:

	Turned on	WiFi off	Mobile data off	Wifi & mobile data off	Turned off (or in flight mode)
Daytime	○	○	○	○	○
When sleeping	○	○	○	○	○

[]Where do you leave your mobile phone **when you go to bed**? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?)

Please choose **only one** of the following:

O In my bed

O On my nightstand

O Somewhere else in my bedroom

O Outside my bedroom

[]Do you use the following functions on your mobile phone? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?) Please choose all that apply:

□ Phone calls

□ Internet voice calls (e.g. Skype, Viber, Whatsapp)

□ Internet video calls (e.g. Skype, Viber, Facetime)

□ Sending SMS

□ Sending voice messages (e.g. Whatsapp, Telegram)

□ Sending video messages (e.g. Snapchat)

□ Sending email

□ Internet browsing

□ Uploading videos and/or pictures

□ Online streaming music (e.g. Spotify, internet radio)

□ Online streaming video (e.g. YouTube, Netflix)

□ Online games (e.g. Draw Something, Wordfeud)

□ As a mobile hotspot (e.g. sharing internet to other devices)

5

[]On average, **how often** do you use the following functions on your mobile phone per day? *

Only answer this question if the following conditions are met:

! is_empty(Q2006_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))
Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

	Less than 1 time per day	1-5 times per day	6-25 times per day	26-50 times per day	more than 50 times per day
Sending SMS	○	○	○	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○	○	○	○
Sending video messages (e.g. Snapchat)	○	○	○	○	○
Sending email	○	○	○	○	○

[]On average, **how often** do you use the following functions on your mobile phone per day? *

Only answer this question if the following conditions are met:

! is_empty(Q2006_1 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_13 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))
Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

	Less than 1 time per day	1-5 times per day	6-15 times per day	16-25 times per day	More than 25 times per day
Phone calls	○	○	○	○	○
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○
Uploading videos and/or pictures	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○
As a mobile hotspot (e.g. sharing internet to other devices)	○	○	○	○	○

[]On average, **how long** do you use the following functions on your mobile phone per day? *

Only answer this question if the following conditions are met:

! is_empty(Q2006_1 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_13 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

	Less than 5 minutes per day	6-30 minutes per day	31-60 minutes per day	1-2 hours per day	More than 2 hours per day
Phone calls	○	○	○	○	○
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○
Internet browsing	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○
As a mobile hotspot (e.g. sharing internet to other devices)	○	○	○	○	○

[]How do you primarily **hold your mobile phone** when using the following functions? *

Only answer this question if the following conditions are met:

! is_empty(Q2006_1 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_13 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

	Against my ear	Less than 20 cm from my eyes	More than 20 cm from my eyes	Hands free / on speaker phone	On my lap	On a surface	In my pocket
Phone calls	○	○	○	○	○	○	○
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○	○	○
Sending SMS	○	○	○	○	○	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○	○	○	○	○	○
Sending video messages (e.g. Snapchat)	○	○	○	○	○	○	○
Sending email	○	○	○	○	○	○	○
Internet browsing	○	○	○	○	○	○	○
Uploading videos and/or pictures	○	○	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○	○	○
As a mobile hotspot (e.g. sharing internet to other devices)	○	○	○	○	○	○	○

[]**Where** do you primarily use the following functions on your mobile phone? *

Only answer this question if the following conditions are met:

! is_empty(Q2006_1 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_13 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

	At home	At work / school
Phone calls	○	○
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○
Sending SMS	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○
Sending video messages (e.g. Snapchat)	○	○
Sending email	○	○
Internet browsing	○	○
Uploading videos and/or pictures	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○
As a mobile hotspot (e.g. sharing internet to other devices)	○	○

[]Which of the following functions do you use in transit (e.g. in a car,on the train)?*

Only answer this question if the following conditions are met:

! is_empty(Q2006_1 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15)) OR ! is_empty(Q2006_13 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/2/qid/15))

Please choose all that apply:

Only answer this question for the items you selected in question Q2006 ('Do you use the following functions on your mobile phone?')

Only answer this question for the items you did not select in question Q2006 ('Do you use the following functions on your mobile phone?')

- ▫ Phone calls
- ▫ Internet voice calls (e.g. Skype, Viber, Whatsapp)
- ▫ Internet video calls (e.g. Skype, Viber, Facetime)
- ▫ Sending SMS
- ▫ Sending voice messages (e.g. Whatsapp, Telegram)
- ▫ Sending video messages (e.g. Snapchat)
- ▫ Sending email
- ▫ Internet browsing
- ▫ Uploading videos and/or pictures
- ▫ Online streaming music (e.g. Spotify, internet radio)
- ▫ Online streaming video (e.g. YouTube, Netflix)
- ▫ Online games (e.g. Draw Something, Wordfeud)
- ▫ As a mobile hotspot (e.g. sharing internet to other devices)

[]On which of the following locations do you use WiFi? (instead of mobile data) *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '10 [Q2001]' (Did you use a mobile phone during the last three months?) Please choose all that apply:

- ▫ At work / school
- ▫ At home
- ▫ In transit
- ▫ In public locations

Your use of tablets

The following questions address your use of tablets.

If you cannot recall, please make a qualified guess.

[]Did you use **a tablet** during the last three months? *

Please choose only one of the following:

- O Yes
- O No

[]How long have you used a tablet? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '23 [Q3001]' (Did you use a tablet during the last three months?)

Please choose only one of the following:

- O Less than 1 year
- O 1 to 4 years
- O 5 to 10 years
- O More than 10 years

[]Do you use the following functions on your tablet? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '23 [Q3001]' (Did you use a tablet during the last three months?)

Please choose all that apply:

- ☐ Internet voice calls (e.g. Skype, Viber, Whatsapp)
- ☐ Internet video calls (e.g. Skype, Viber, Facetime)
- ☐ Sending SMS
- ☐ Sending voice messages (e.g. Whatsapp, Telegram)
- ☐ Sending video messages (e.g. Snapchat)
- ☐ Sending email
- ☐ Internet browsing
- ☐ Uploading videos and/or pictures
- ☐ Online streaming music (e.g. Spotify, internet radio)
- ☐ Online streaming video (e.g. YouTube, Netflix)
- ☐ Online games (e.g. Draw Something, Wordfeud)

[]On average, **how often** do you use the following functions on your tablet per day? *

Only answer this question if the following conditions are met:

! is_empty(Q3003_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

	Less than 1 time per day	1-5 times per day	6-25 times per day	26-50 times per day	More than 50 times per day
Sending SMS	○	○	○	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○	○	○	○
Sending video messages (e.g. Snapchat)	○	○	○	○	○
Sending email	○	○	○	○	○

[]On average, **how often** do you use the following functions on your tablet per day? *

Only answer this question if the following conditions are met:

! is_empty(Q3003_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

	Less than 1 time per day	1-5 times per day	6-15 times per day	16-25 times per day	More than 25 times per day
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○
Uploading videos and/or pictures	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○

[]On average,**how long** do you use the following functions on your tablet per day?*

Only answer this question if the following conditions are met:

! is_empty(Q3003_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

	Less than 5 minutes per day	6-30 minutes per day	31-60 minutes per day	1-2 hours per day	More than 2 hours per day
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○
Internet browsing	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○

[]How do you primarily **hold your tablet** when using the following functions? *

Only answer this question if the following conditions are met:

! is_empty(Q3003_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

	Against my ear	Less than 20 cm from my eyes	More than 20 cm from my eyes	Hands free / on speaker phone	On my lap	On a surface
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○	○	○	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○	○	○	○	○
Sending SMS	○	○	○	○	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○	○	○	○	○
Sending video messages (e.g. Snapchat)	○	○	○	○	○	○
Sending email	○	○	○	○	○	○

5

Internet browsing	○	○	○	○	○	○
Uploading videos and/or pictures	○	○	○	○	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○	○	○	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○	○	○	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○	○	○	○	○

[]**Where** do you primarily use the following functions on your tablet? *

Only answer this question if the following conditions are met:

! is_empty(Q3003_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose the appropriate response for each item:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

	At home	At work / school
Internet voice calls (e.g. Skype, Viber, Whatsapp)	○	○
Internet video calls (e.g. Skype, Viber, Facetime)	○	○
Sending SMS	○	○
Sending voice messages (e.g. Whatsapp, Telegram)	○	○
Sending video messages (e.g. Snapchat)	○	○
Sending email	○	○
Internet browsing	○	○
Uploading videos and/or pictures	○	○
Online streaming music (e.g. Spotify, internet radio)	○	○
Online streaming video (e.g. YouTube, Netflix)	○	○
Online games (e.g. Draw Something, Wordfeud)	○	○

[]Which of the following functions do you use **in transit** (e.g.in a car, on the train)?*

Only answer this question if the following conditions are met:

! is_empty(Q3003_2 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_3 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_4 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_5 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_6 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_7 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_8 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_9 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_10 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_11 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24)) OR ! is_empty(Q3003_12 (/index.php?r=admin/questions/sa/view/surveyid/315829/gid/3/qid/24))

Please choose all that apply:

Only answer this question for the items you selected in question Q3003 ('Do you use the following functions on your tablet?')

Only answer this question for the items you did not select in question Q3003 ('Do you use the following functions on your tablet?')

- ☐ Internet voice calls (e.g. Skype, Viber, Whatsapp)
- ☐ Internet video calls (e.g. Skype, Viber, Facetime)
- ☐ Sending SMS
- ☐ Sending voice messages (e.g. Whatsapp, Telegram)
- ☐ Sending video messages (e.g. Snapchat)
- ☐ Sending email
- ☐ Internet browsing
- ☐ Uploading videos and/or pictures
- ☐ Online streaming music (e.g. Spotify, internet radio)
- ☐ Online streaming video (e.g. YouTube, Netflix)
- ☐ Online games (e.g. Draw Something, Wordfeud)

[]On which of the following locations do you use WiFi? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '23 [Q3001]' (Did you use a tablet during the last three months?)

Please choose all that apply:

- ☐ At work / school
- ☐ At home
- ☐ In transit
- ☐ In public locations

Your use of laptops

The following questions address your use of laptops during the last three months. This also includes netbooks and ultrabooks.

If you cannot recall, please make a qualified guess.

[]Do you use a laptop with wireless access to the internet, for at least an hour per week? *

Please choose **only one** of the following:

O Yes

O No

[]How many **hours per day** do you use wireless access to the internet on your laptop, on a typical day? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '33 [Q4001]' (Do you use a laptop with wireless access to the internet, for at least an hour per week?) Please choose only one of the following:

O None or almost none

O Less than 1 hour

O 1-3 hours

O 4-6 hours

O 7-9 hours

O More than 10 hours

[]On which of the following locations do you **use wireless access** to the internet on your laptop? *

Only answer this question if the following conditions are met:

Answer was 'Yes' at question '33 [Q4001]' (Do you use a laptop with wireless access to the internet, for at least an hour per week?) Please choose all that apply:

□ At work / school

□ At home

□ In transit

□ In public locations

Your use of other devices

The following questions address your use of other devices during the last three months.

If you cannot recall, please make a qualified guess.

[]On average, **how long** do you use the following devices per day? *

Please choose the appropriate response for each item:

	I don’t use this	Less than 8 hours per day	8-16 hours per day	16-24 hours per day
Activity/life trackers (e.g. Jawbone, Fitbit)	○	○	○	○
Body-worn sensors (e.g. medical sensors)	○	○	○	○
Smart watches	○	○	○	○

[]On average, **how long** do you use the following devices per day? *

Please choose the appropriate response for each item:

	I don’t use this	Less than 5 minutes per day	6-30 minutes per day	31-60 minutes per day	1-2 hours per day	More than 2 hours per day
VR headsets (e.g. Samsung Gear VR)	○	○	○	○	○	○
WiFi enabled portable media players (e.g. iPod Touch)	○	○	○	○	○	○
E-readers	○	○	○	○	○	○
Other mobile devices	○	○	○	○	○	○

5

Final questions

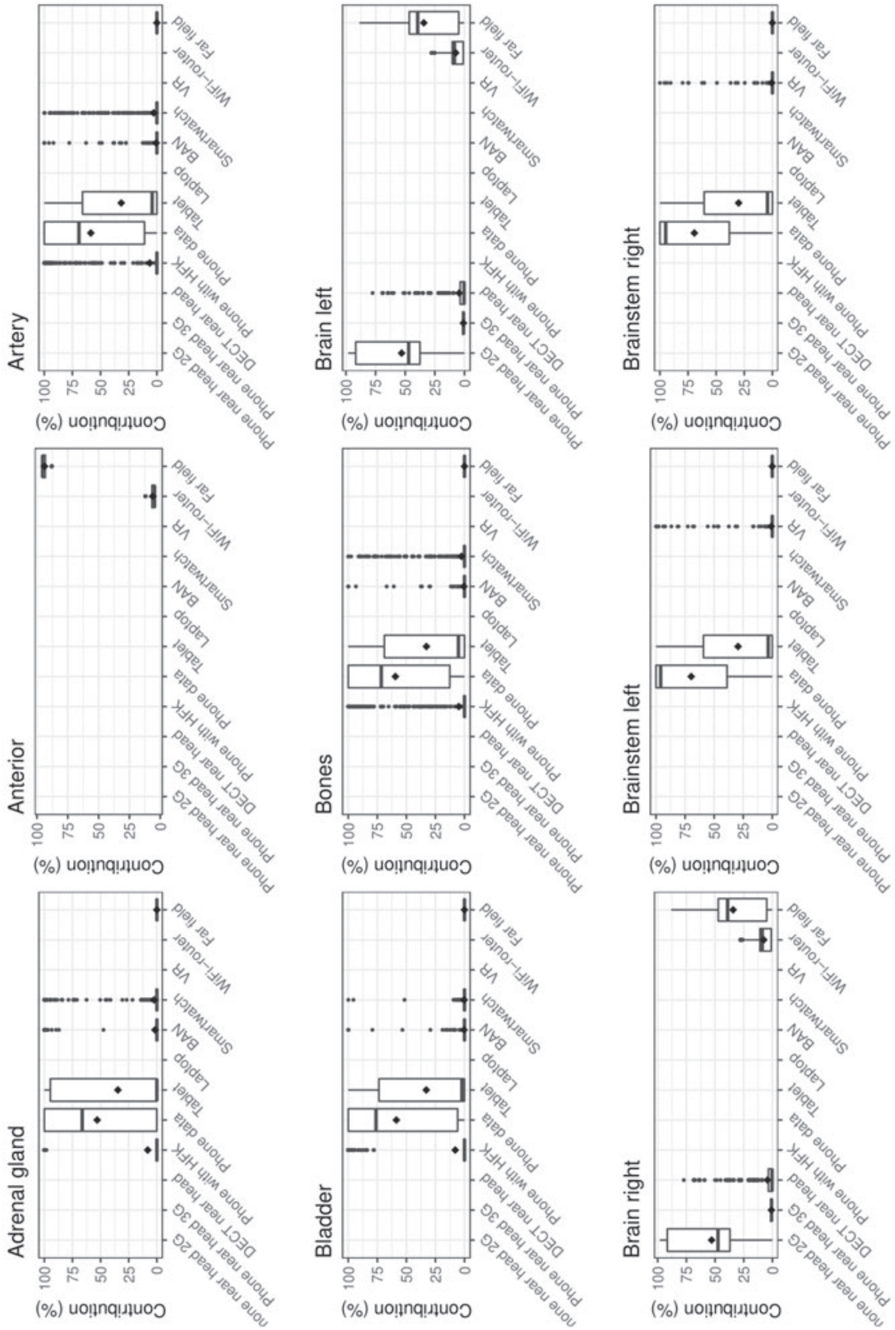
[]If you have any comments for us you are welcome to write them in the space below:

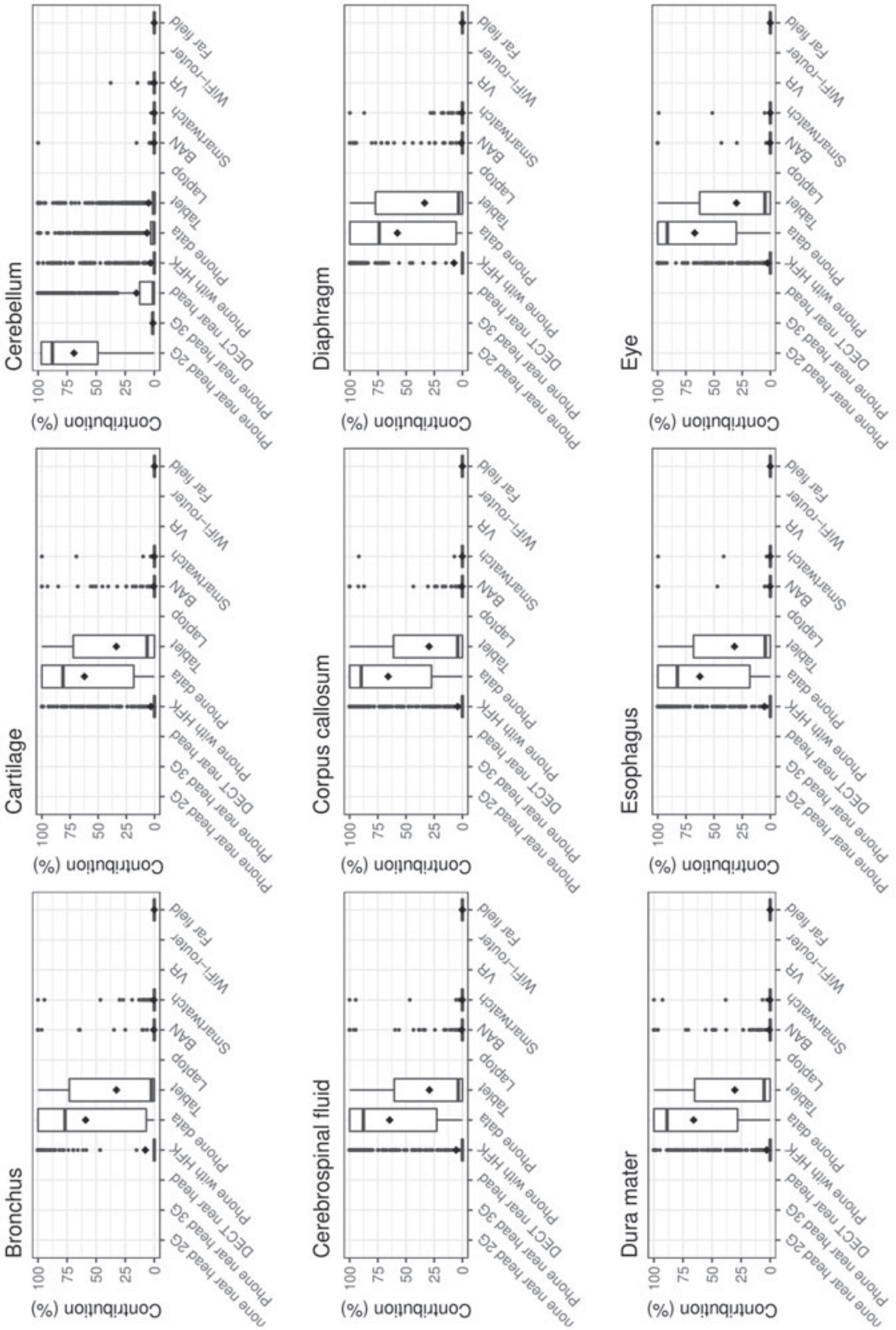
Please write your answer here:

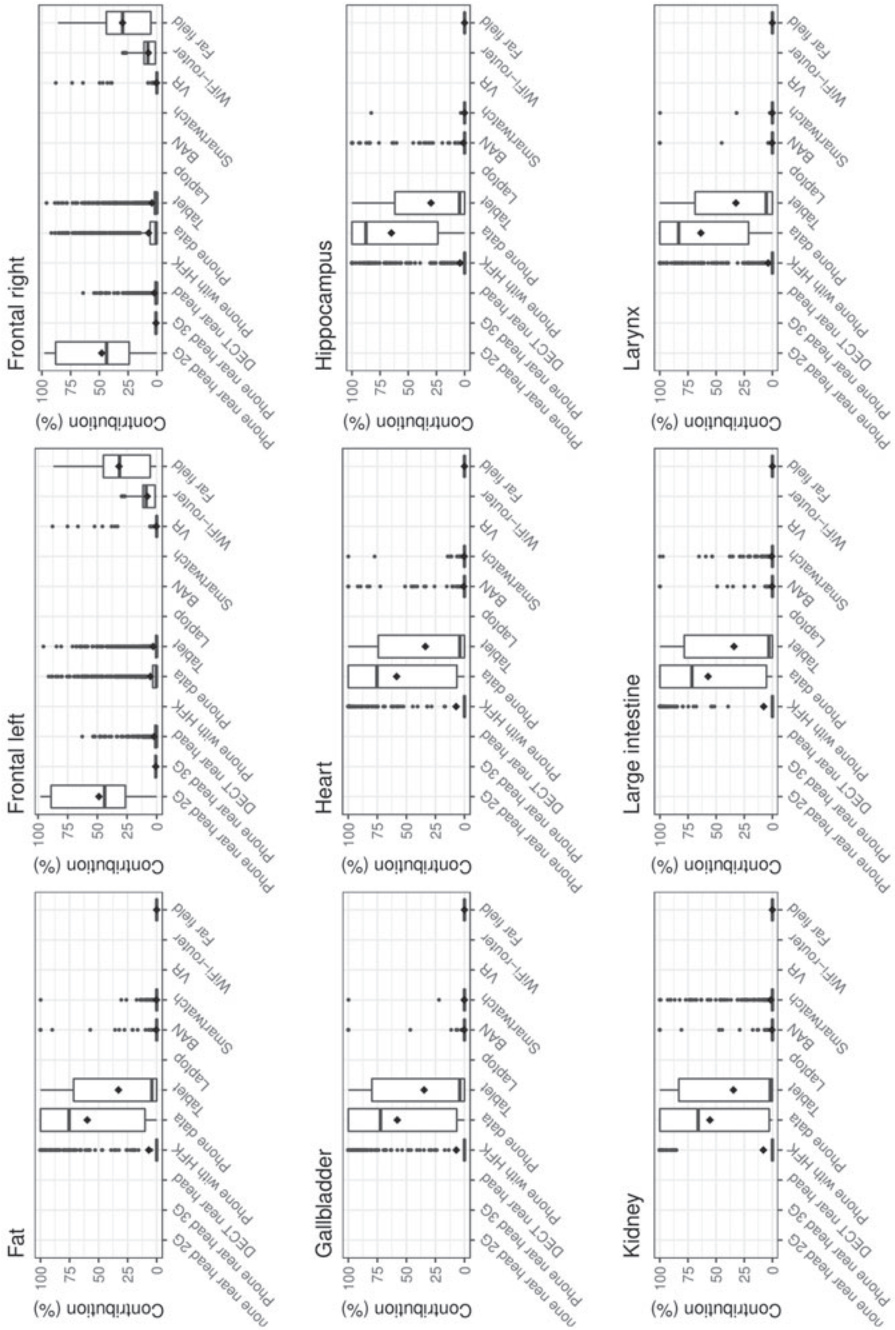
Thank you for filling in our questionnaire. Your answeres have been saved and you can now close this window.

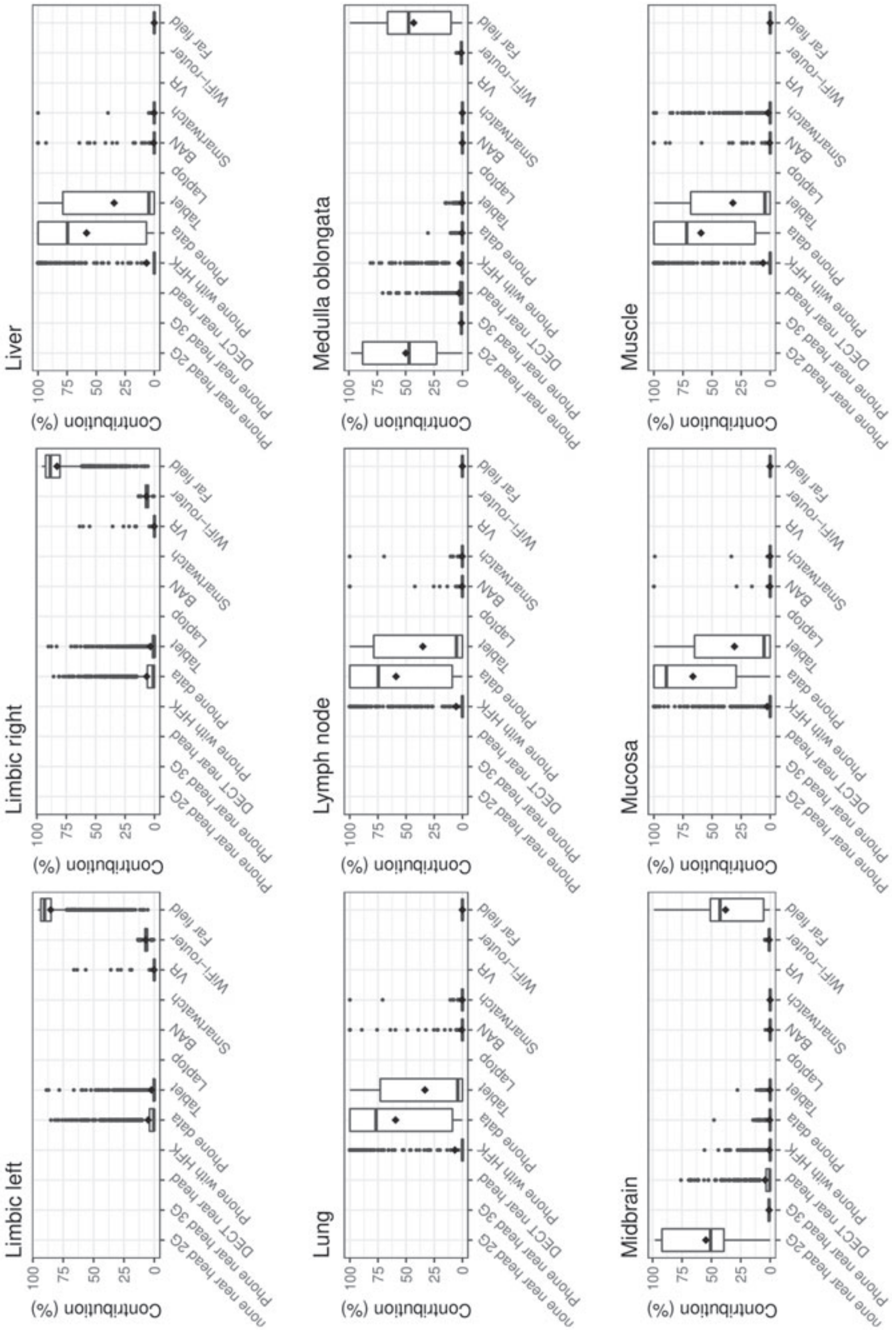
Submit your survey.

Thank you for completing this survey.


Adrenal gland
Anterior
Artery
Bladder
Bones
Brain left
Brain right
Brainstem left
Brainstem right
Contribution (%)
0
25
50
75
100
Phone near head 2G
DECT near head 3G
Phone near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

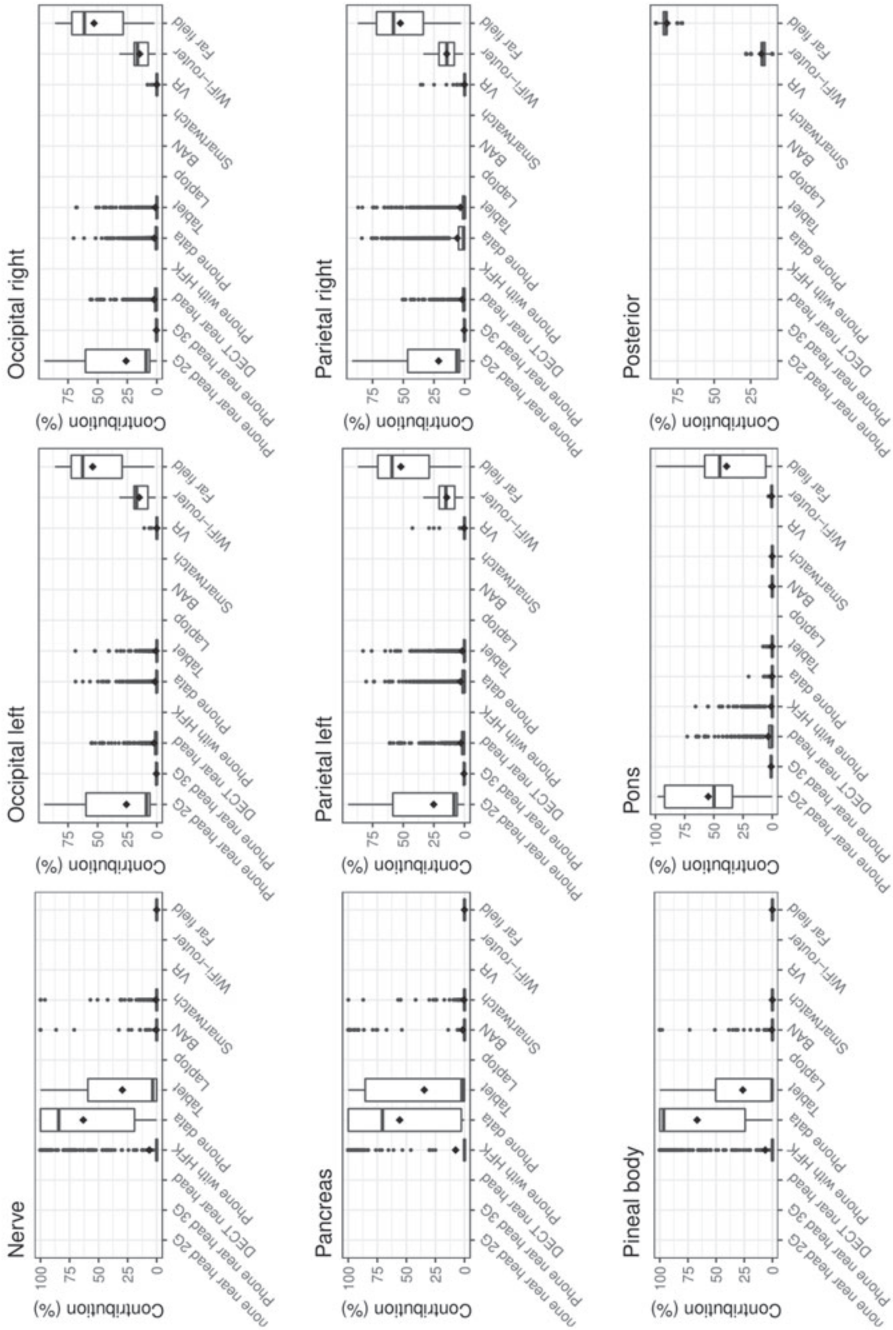

Cerebellum
Cartilage
Bronchus
Diaphragm
Corpus callosum
Cerebrospinal fluid
Eye
Esophagus
Dura mater
Contribution (%)
0
25
50
75
100
none
Phone near head 2G
Phone near head 3G
DECT near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

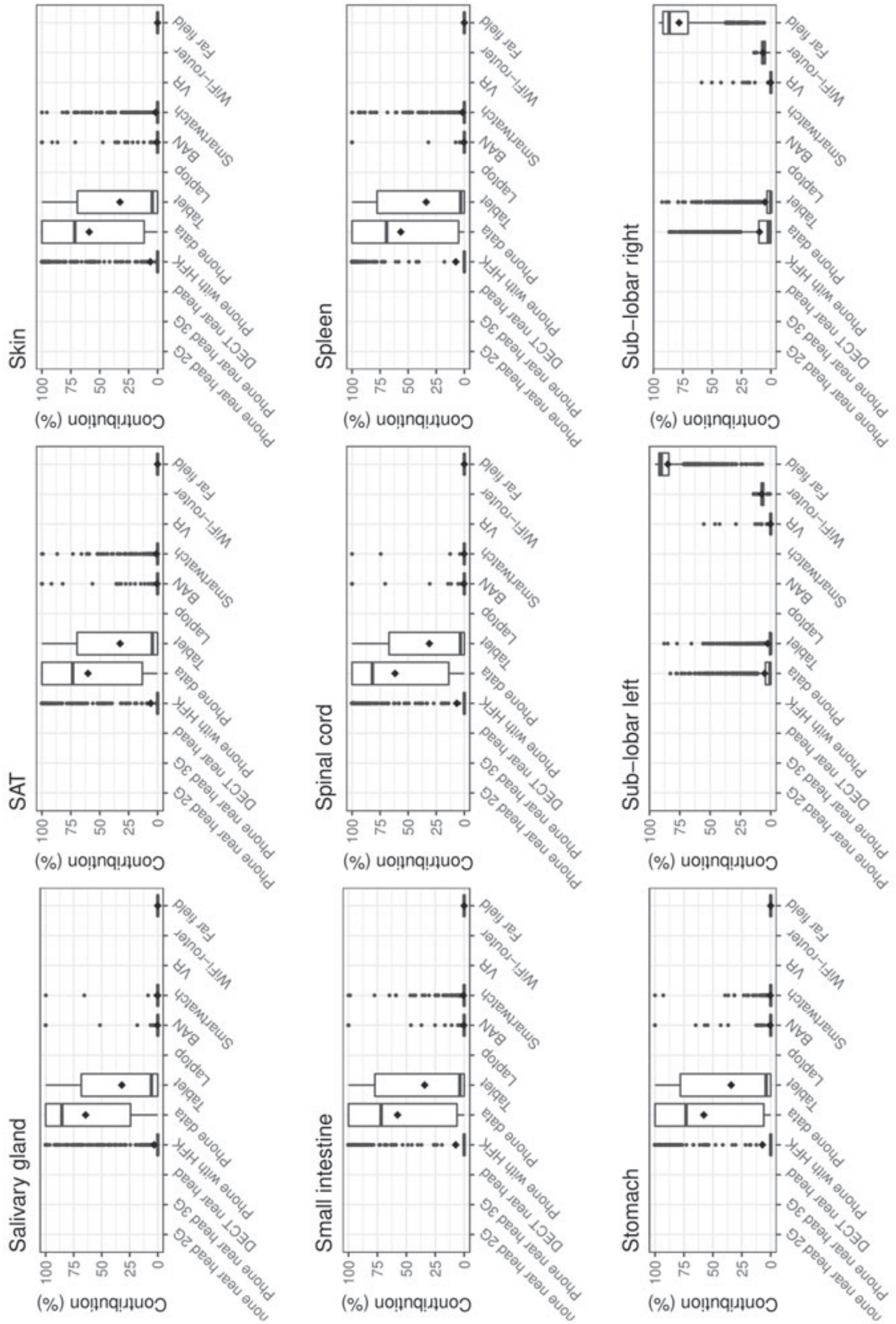

Frontal right
Frontal left
Fat
Hippocampus
Heart
Gallbladder
Larynx
Large intestine
Kidney
Contribution (%)
0
25
50
75
100
Phone near head 2G
DECT near head 3G
Phone near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field



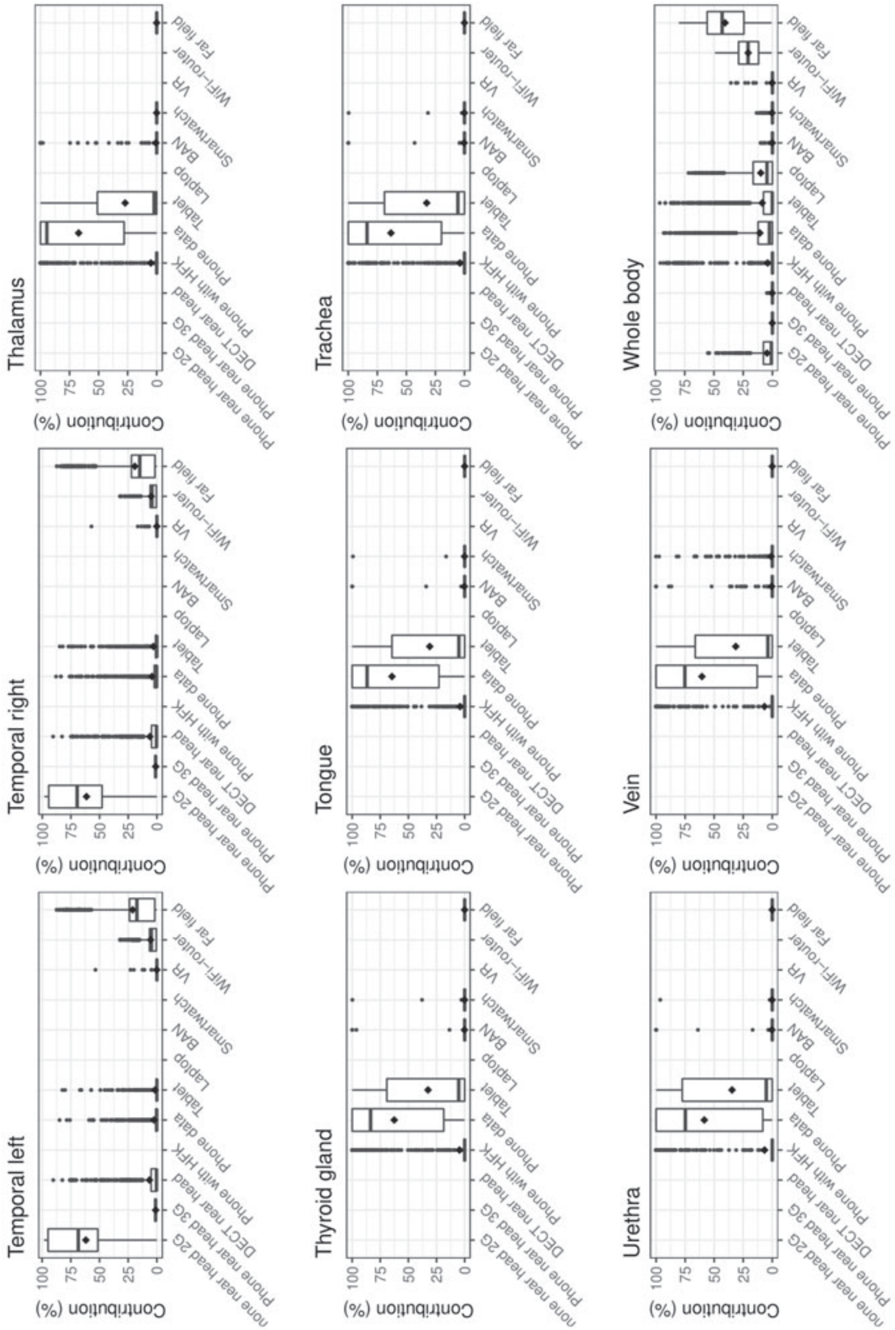
Limbic left
Limbic right
Liver
Lung
Lymph node
Medulla oblongata
Midbrain
Mucosa
Muscle
Contribution (%)
100
75
50
25
0
none
Phone near head 2G
DECT near head 3G
Phone near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

5


Nerve
Occipital left
Occipital right
Pancreas
Parietal left
Parietal right
Pineal body
Pons
Posterior
Contribution (%)
Phone near head 2G
DECT near head 3G
Phone near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

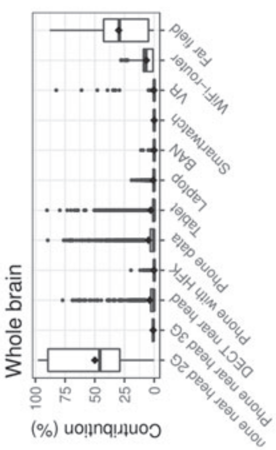

Salivary gland
SAT
Skin
Small intestine
Spinal cord
Spleen
Stomach
Sub−lobar left
Sub−lobar right
Contribution (%)
0
25
50
75
100
Phone near head 2G
Phone near head 3G
DECT near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi−router
Far field

5


Temporal left
Temporal right
Thalamus
Thyroid gland
Tongue
Trachea
Urethra
Vein
Whole body
Contribution (%)
100
75
50
25
0
Phone near head 2G
Phone near head 3G
DECT near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

5

5


Whole brain
Contribution (%)
100
75
50
25
0
none near head 2G
Phone near head 3G
DECT
Phone near head
Phone with HFK
Phone data
Tablet
Laptop
BAN
Smartwatch
VR
WiFi–router
Far field

CHAPTER 6

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

Luuk van Wel, Anke Huss, Philipp Bachmann, Marco Zahner, Hans Kromhout,
Jürg Fröhlich, Roel Vermeulen.

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Abstract

Introduction Modern sensor technology makes it possible to collect vast amounts of environmental, behavioural and health data. These data are often linked to contextual information on for example exposure sources which is separately collected with considerable lag time, leading to complications in assessing transient and/or highly spatially variable environmental exposures. Context-Sensitive Ecological Momentary Assessments (CS-EMAs) could be used to address this. We present a case study using radiofrequency-electromagnetic fields (RF-EMF) exposure as an example for implementing CS-EMA in environmental research.

Methods Participants were asked to install a custom application on their own smartphone and to wear an RF-EMF exposimeter for 48 hours. Questionnaires were triggered by the application based on a continuous data stream from the exposimeter. Triggers were divided into four categories: relative and absolute exposure levels, phone calls, and control condition. After the two days of use participants filled in an evaluation questionnaire.

Results 74% of all CS-EMAs were completed, with an average time of 31 seconds to complete a questionnaire once it was opened. Participants reported minimal influence on daily activities. There were no significant differences found between well-being and type of RF-EMF exposure.

Conclusions We show that a CS-EMA based method could be used in environmental research. Using several examples involving environmental stressors, we discuss both current and future applications of this methodology in studying potential health effects of environmental factors.

Introduction

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

Ecological momentary assessment (EMA) encompasses a range of data collection methodologies used in, amongst others, clinical psychology. Key aspects of EMA are the repeated collection of data under real-world environment conditions, close in time to an event, and at strategically selected moments (1-2). Depending on the event of interest, triggers for assessments can take place at set intervals, at random moments of the day, at predefined events or following some other sampling scheme. More recently, context-sensitive ecological momentary assessments (CS-EMAs) have been introduced. CS-EMA is an extension of the classic EMA methodology in which a data stream is used to determine the moment of assessment (3). For example, Dunton *et al.*(4) used the smartphone's internal motion sensor to trigger momentary assessments when a predefined amount of physical activity had been detected. The advantages of (CS-)EMA include a better recall due to the short time period between the event of interest and the assessment, and the ability to collect data in the natural, real-life environment of a subject.

The ability to continuously collect and process large amounts of data on environmental parameters, in combination with CS-EMA approaches could be used to identify exposure sources and to explore potential health effects related to environmental factors. We carried out a case study in which we developed a smartphone application capable of processing incoming data in real-time, using exposure levels to trigger momentary assessments. We used exposure to radiofrequency electromagnetic fields (RF-EMF) as a test case. RF-EMF is highly

spatially variable and there have been reports of individuals ascribing a variety of health problems to exposure to RF-EMF (also called electromagnetic hypersensitivity). Frequently reported symptoms include concentration problems, headache, nervousness and fatigue, often occurring within minutes of exposure (5). Previous studies have investigated such effects in controlled laboratory studies. However, these studies have been criticized because usually just one exposure was applied, whereas real-life exposures would represent a mix of different types of frequencies and signal types. Therefore, the use of an EMA design, where the real-life environment is a key aspect, could provide an informative way to study this association. A similar concept has been tried by bogers *et al.*(6), who performed a study where continuous collection of radiofrequency electromagnetic field (RF-EMF) data was combined with a random trigger EMA design. In this study design, the RF-EMF exposure levels did however not trigger the assessments, making it difficult to collect sufficient assessments on less common events.
The aim of the presented study is to test the technical feasibility of CS-EMA by real-time processing of environmental sensor data, the adherence to assessments whose triggers are based on sensor data, and the influence on daily activities of participants using RF-EMF exposure as a test case.

Methods

Study population and protocol

Participants were recruited from the city of Utrecht (the Netherlands) and its surrounding area between May and October 2015. Eligibility criteria included being at least 18 years of age, using a smartphone running the Android operating system, and being able to understand the Dutch language. Participants were recruited via an online portal (www.proefbunny.nl) and obtained a small monetary compensation for their efforts. Two appointments, 48 hours apart, were made with each participant. During the first appointment the custom smartphone application (ExpoMDiary) was installed on the participants own smartphone, and the RF-EMF exposimeter was handed out. Participants were instructed to wear the RF-EMF exposimeter between the two appointments and to answer the triggered questionnaires when possible. Each participant was provided with a small bag to carry the RF-EMF exposimeter at the hip level as previously described by Martens *et al.* (7). Equipment and data was retrieved during the second appointment and the participant was asked to fill out a short evaluation questionnaire. The evaluation questionnaire consisted of questions regarding the amount of time the devices were carried, the perceived influence on daily activities, and whether the participant had ever linked health problems to RF-EMF exposure. The medical ethical committee of the University Medical Center Utrecht (UMCU) reviewed the study protocol and concluded that further ethical approval was not required.

RF-EMF exposimeter

An ExpoM - RF exposimeter (Fields at Work GmbH, Switzerland) was used to monitor RF-EMF exposure. The device is capable of simultaneously monitoring 16 different frequency bands, covering the most relevant RF-EMF sources with a high sensitivity (8). Detailed specifications are provided in Supplementary Materials Table S6.1. Samples were taken once every eight seconds and subsequently transmitted to the smartphone application via Bluetooth. Data transmission took less than 100 milliseconds, was performed between the measurement intervals and thus did not interfere with measurements taken. Smartphone and exposimeter had to be within three to four metres of each other to transfer data, depending on the environmental conditions (i.e., line of sight, smartphone cover).

ExpoMDiary application

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

Questionnaire trigger conditions

A questionnaire assessment was triggered when one of the primary and all of the secondary conditions were met. Four events were specified as primary conditions: 1) a sudden relative increase in exposure, 2) exposure exceeding an absolute threshold, 3) an incoming or outgoing phone call, or 4) no questionnaires triggered for the past 1.5 hours (control event). Sudden relative increase was defined as a tenfold increase in power density (mW/m^2) compared to the moving average of the past half hour. The threshold for the absolute exposure level was set at 10 mW/m^2 (1.94 V/m). This is roughly a quarter of the maximum power density observed by Joseph *et al*. (40.4 mW/m^2 (3.9 V/m)) during in-situ measurement in the Netherlands, Belgium and Sweden 9). Phone calls are particular events of interest as the phone is typically held close to the head during these events, causing higher exposure levels to the brain. The questionnaire would appear after the phone call was finished. Secondary conditions were specified as not to overburden the participants. To allow undisturbed sleep, no questionnaires were triggered between 10pm and 8am. Minimum wash-out period between answered questionnaires was 45 minutes. Lastly, no more than 10 questionnaires were triggered on a particular day. Ignored or missed questionnaires did not count towards this total of 10 questionnaires per day. Triggers followed a first come, first serve hierarchy where the first valid trigger would be used, regardless of the previous type or number of triggers during the day.

Questionnaires

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

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

Statistical analysis

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

Results

We obtained useable data on 34 out of 46 participants. Twelve unusable datasets were excluded due to technical failures in communication between the exposimeter and the smartphone application, resulting in none or few collected questionnaires. These issues were subsequently patched in later versions of the application. The 34 participants were on average 32 years old (range 18-59). There were 15 male (44%) and 19 female (56%) participants. None of the participants reported ever having attributed health related problems to RF-EMF exposure (electromagnetic hypersensitivity). Radiofrequency electromagnetic field exposures were on average 187 $\mu W/m^2$ (interquartile range (IQR) 91 - 235) (Supplementary Materials Table S6.2).

Compliance and trigger distribution

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

The main trigger reason was a tenfold relative increase in average power density (60.4%), followed by the control condition (28.5%). Only one phone call event triggering a questionnaire occurred. The distribution of trigger reasons for completed questionnaires was similar (Figure 6.1).

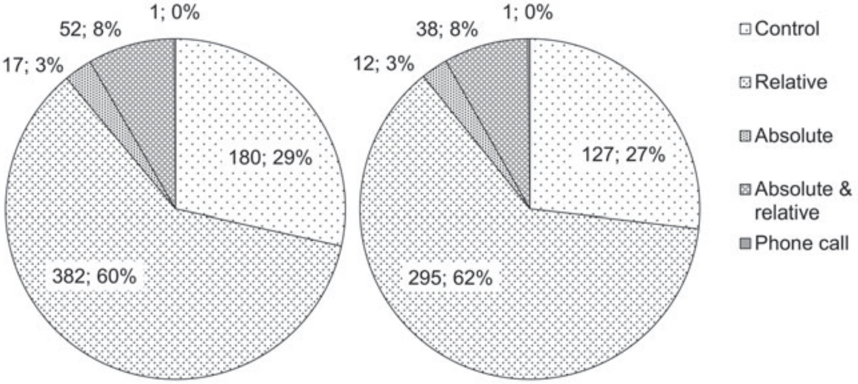

Figure 6.1: Distribution of trigger reasons. All triggered questionnaires on the left versus completed questionnaires on the right.

Questionnaire outcomes

The results of the nine questions on wellbeing and symptoms are shown in Figure 6.2, stratified by the type of exposure that triggered the questionnaire. No significant differences in symptom or well-being scores across the exposure triggers were observed. Other reported symptoms included having a cold, minor back pain, and muscle aches.

Discussion

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

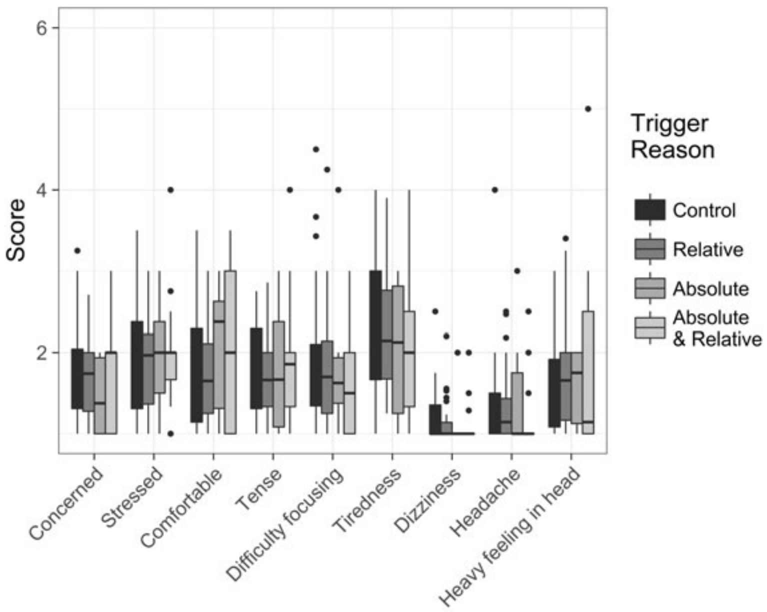

Figure 6.2: Results of nine symptom-based questions, stratified for trigger reason.

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

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

Lessons learnt

Despite being one of the primary conditions specified, a phone call event only once triggered a questionnaire. The reason for this can be found in the secondary conditions we set up. After each completed questionnaire no other questionnaire would happen for 45 minutes, and if none happened after 90 minutes the control condition would be triggered. This leaves effectively a 45-minute window for a relative, absolute, or phone call event to occur. It turned out that a relative or absolute event would occur more often than a phone call event, each time resetting the 45-minute wash-out. This example from the test case shows that it is of great importance to carefully consider the primary and secondary trigger conditions. One possible solution would be to allow for a maximum number of questionnaires per trigger conditions, thus opening up space for other less frequent trigger conditions to actually trigger a questionnaire.
Secondly, we used the own smartphone of a participant to run our application instead of providing a separate device. Benefits included the ability to use information from the participants' own smartphone (i.e., incoming and outgoing phone calls) and only one additional device to carry around for the participant,

the exposimeter. However, this also meant that we had to ensure compatibility between the application and a wide range of Android hardware and software versions. While we were able to patch unforeseen compatibility issues in subsequent versions it meant the loss of some datasets. Clearly, for any future study not addressing RF-EMF exposure, researchers could consider using identical study phones, although this comes at the drawback of an additional device that needs to be carried around by a participant resulting potentially in less adherence to the study protocol.

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

Future applications

We presented here a test case showing a potential use of CS-EMA methodology in environmental health research, using continuous data streams from both an external sensor and from the smartphone itself. However, this application is not limited to one or two data streams: there are currently a wide range of real-time sensors available, from EMF exposimeters, health sensors (e.g. heart rate), to personal activity trackers. At the same time, the current generation of smartphones provides an affordable and flexible platform to use and analyse data from these sensors. In addition, current smartphones have enough processing power to handle multiple data streams in real-time and various sensors are already built in (e.g., motion detection, GPS positioning), and standard Bluetooth connectivity allows for easy connection of multiple external sensors. While in our application the data was not streamed directly to study servers for additional analyses such an addition can be easily implemented. For example, the recently developed XMobiSense smartphone application (10), capable of monitoring mobile phone usage and user behaviour data, was updated to stream data directly to study servers. Further updates will allow modifications to the application protocol without having to return to the research institute.

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

Air pollution

Current studies are gathering vast amounts of information on personal air pollution exposure, with a multitude of sensors available to continuously gather data. One such example is the EXPOsOMICS project, where participants carry around a backpack containing air pollution sensors as well as a belt containing a smartphone tracking their location and activity levels (11). This smartphone platform could be adapted to read and interpret the sensor data stream in real-time, allowing for a CS-EMA setup that further investigated acute effects of air pollution exposure. This includes, but is not limited to evaluating individual thresholds of health responses to air pollution levels or to ascertain immediacy or time period until a health response is triggered. A similar concept has been explored by Spira-Cohen *et al*. (12), where children carried around a backpack with a variety of samplers. Respiratory symptoms were scored and spirometry measurements performed at set intervals during the day. Using a CS-EMA methodology this can be taken one step further by selecting key moments for symptom scoring and spirometry measurement based on the levels of air pollutants in real-time while also tracking activity using either questions in the assessments or an activity/GPS tracker.

RF-EMF

A natural extension of the CS-EMA approach presented here would be to trigger at specific types of RF-signals that some people report reacting to (e.g. specifically testing WiFi or DECT phone signals). Also, RF-EMF exposure originates from a variety of indoor and outdoor sources, causing complex exposure patterns. Our CS-EMA approach enables linkage of the exposimeter-data to evaluate exposure patterns of interest. When a predefined pattern appears, the questions are not necessarily limited to current wellbeing. Questions regarding details of the current situation, supplemented by GPS coordinates and photographs taken from the surrounding could be included as well. The information could subsequently be used to better interpret observed exposure patterns. This could provide a much more detailed description than a continuous diary as applied by previous researchers 13).

Noise

Noise is a widespread environmental factor with high spatial variation and the ability to cause both auditory and non-auditory health effects. There is uncertainty whether specific noise characteristics (e.g. noise frequency spectrum of the sound, intermittency, maximum sound pressure) may be more relevant for health effects rather than average noise levels (14). Using a noise sensor in combination with a sophisticated protocol interpreting multiple noise characteristics, health as well as annoyance assessments could be triggered following exposure to any desired combination of noise characteristics. Such an evaluation could be supplemented by obtaining objective stress measurements via skin conductivity and heart rate variability sensors to further elucidate the effects of noise on health.

Odour

Odorants can influence human health via both physical mechanism and via annoyance with large variability in sensitivity to and annoyance from exposure to odours (15). Studies into these effects often use medical records, geographical information systems and paper questionnaires to gather information (16). With the continued development of odour sensors, so called electronic noses, we may expect a future odour sensor which can reliably detect odour levels (17). The use of such a sensor to gather objective odour data, in combination with a CS-EMA based assessment on annoyance, could help to disentangle effects of annoyance from other mechanisms through which odorants affect human health.

Capturing multiple determinants

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

Conclusion

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

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Supplementary Materials

Questionnaire

Each questionnaire contained the following questions in Dutch. Both the original Dutch version and the translated English version are included here.

English
Question 1: How do you feel at this moment?
Concerned 1 - Completely unconcerned, 6 - very concerned
Stressed 1 - Completely relaxed, 6 - Completely stressed
Comfortable 1 - Very comfortable, 6 - Very uncomfortable
Tense 1 - Completely relaxed, 6 - Very tense

Question 2: Do you experience the following symptoms?
Difficulty focussing 1 - No difficulty, 6 - Very difficult
Tiredness 1 - Not tired, 6 - Very tired
Dizziness 1 - Not dizzy, 6 - Very dizzy
Headache 1 - No headache, 6 - Strong headache
Heavy feeling in head 1 - Clear, 6 - Very dull/pressing feeling

Question 3: Do you currently have any other symptoms?
open text

Question 4: Where are you right now?
At home / At work / In transit / Train station / Shopping / Sport / Elsewhere

Dutch
Vraag 1: Hoe voelt u zich op dit moment?
Bezorgd 1 - compleet onbezorgd, 6 - zeer bezorgd
Gespannen / gestressed 1 - compleet ontspannen, 6 - zeer gespannen
Lichamelijk comfortabel 1 - zeer comfortabel, 6 - zeer oncomfortabel
Lichamelijk gespannen 1 - compleet ontspannen, 6 - zeer gespannen

Vraag 2: Ervaart u de volgende symptomen?
Moeite met concentreren 1 - geen moeite, 6 - veel moeite
Vermoeidheid 1 - niet vermoeid, 6 - zeer vermoeid
Duizeligheid 1 - niet duizelig, 6 - zeer duizelig

Hoofdpijn 1 – geen hoofdpijn, 6 – veel hoofdpijn
Zwaar gevoel in het hoofd 1 - helder, 6 - zeer dof/drukkend gevoel

Vraag 3: Heeft u op dit moment andere symptomen?
open invulmogelijkheid

Vraag 4: Waar bent u op dit moment?
Thuis / Werk / Onderweg / Treinstation / Winkel / Sport / Anders

Table S6.1: Fields at Work ExpoM RF frequency bands and detection limits.

Frequency band	Frequency range	Lower detection limit
FM radio	87.5 – 108 MHz	0.02 V/m
DVB-T (digital television)	470 – 790 MHz	0.005 V/m
Mobile 800 MHz uplink	832 – 862 MHz	0.005 V/m
Mobile 800 MHz downlink	791 – 821 MHz	0.005 V/m
Mobile 900 MHz uplink	880 – 915 MHz	0.005 V/m
Mobile 900 MHz downlink	925 – 960 MHz	0.005 V/m
Mobile 1800 MHz uplink	1710 – 1785 MHz	0.005 V/m
Mobile 1800 MHz downlink	1805 – 1880 MHz	0.005 V/m
DECT (cordless home phones)	1880 – 1900 MHz	0.005 V/m
Mobile 2.1 GHz uplink	1920 – 1980 MHz	0.003 V/m
Mobile 2.1 GHz downlink	2110 – 2170 MHz	0.003 V/m
ISM 2.4 GHz	2400 – 2485 MHz	0.005 V/m
Mobile 2.6 GHz uplink	2500 – 2570 MHz	0.003 V/m
Mobile 2.6 GHz downlink	2620 – 2690 MHz	0.003 V/m
Mobile 3.5 GHz	3400 – 3600 MHz	0.003 V/m
ISM 5.8 GHz	5150 – 5875 MHz	0.05 V/m

Table S6.2: 45 useable RF-EMF exposure datasets were obtained during the case study. A summary is provided in the following table. All values are in μW/m^2.

Frequency band	Frequency Range	Mean	P5	P25	Median	P75	P95
FM radio	87.5 – 108 MHz	22.9	0.2	2.7	8.8	20.3	97.3
DVB-T (digital television)	470 – 790 MHz	15.6	0.8	3.1	6.7	13.4	56.7
Mobile 800 MHz downlink	791 – 821 MHz	8.1	0.7	2.7	5.2	9.2	26.5
Mobile 800 MHz uplink	832 – 862 MHz	0.9	0.0	0.0	0.1	0.2	1.3
Mobile 900 MHz uplink	880 – 915 MHz	19.9	0.1	0.4	3.4	8.4	67.4
Mobile 900 MHz downlink	925 – 960 MHz	23.4	4.7	10.4	19.1	26.0	72.8
Mobile 1800 MHz uplink	1710 – 1785 MHz	10.7	0.0	0.3	0.7	4.7	57.7
Mobile 1800 MHz downlink	1805 – 1880 MHz	32.6	1.2	4.5	10.2	19.3	73.1
DECT (cordless home phones)	1880 – 1900 MHz	5.2	0.5	1.2	2.6	4.3	18.0
Mobile 2.1 GHz uplink	1920 – 1980 MHz	18.0	0.1	1.3	5.2	20.2	80.8
Mobile 2.1 GHz downlink	2110 – 2170 MHz	12.2	1.6	3.6	7.8	15.1	32.8
ISM 2.4 GHz	2400 – 2485 MHz	12.3	2.1	3.6	6.2	10.0	35.8
Mobile 2.6 GHz uplink	2500 – 2570 MHz	0.0	0.0	0.0	0.0	0.0	0.0
Mobile 2.6 GHz downlink	2620 – 2690 MHz	0.3	0.0	0.0	0.1	0.3	0.8
Mobile 3.5 GHz	3400 – 3600 MHz	0.0	0.0	0.0	0.0	0.0	0.1
ISM 5.8 GHz	5150 – 5875 MHz	4.6	0.1	0.5	1.3	4.5	14.5
Total		186.9	48.8	90.8	141.6	235.2	571.3

CHAPTER 7

General discussion

The aim of this thesis was to explore the challenges in assessment of exposure to radiofrequency electromagnetic fields (RF-EMF) and to propose and study improved (integrative) individual exposure assessment methodologies. RF-EMF exposure monitor measurements, mobile phone use recall versus network operator data, and mobile phone use recall versus software-modified phones (SMPs) were explored to achieve the first part of this aim. The findings showed various difficulties involving RF-EMF exposure assessment, which will be discussed in more detail in this chapter.

For the second part of this thesis' aim, an integrated exposure assessment model and a novel method for evaluating short-term health effects were developed. The Integrated Exposure Model (IEM) combined questionnaire data and measurement information from multiple exposure sources to come to individual dose estimations for multiple anatomical sites. Secondly, a context-sensitive ecological momentary assessment (CS-EMA) based platform was developed where real-time measurement data were used to collect assessments on well-being directly after elevated RF-EMF exposures, aiding in the assessment of potential short-term health effects.

In this chapter I will discuss the challenges explored in the various aspects of RF-EMF exposure assessment, followed by the abovementioned IEM model and CS-EMA method. Lastly, an outlook on the future of RF-EMF exposure assessment in the context of epidemiological studies involving health effects will be provided.

RF-EMF exposure assessment

There are many sources of radiofrequency electromagnetic fields exposure in modern society, each potentially contributing to your daily exposure and consequently dose. The level of exposure from one single source may be little, but together they can be substantial. We therefore want to include all relevant RF-EMF sources in our exposure assessment. The resulting exposure levels can then be related to potential short- and long-term health effects in epidemiological studies. There are many factors influencing exposure levels: number of sources, near- or far-field, position relative to the subject of interest, the way the source is being used (e.g., calling, streaming, broadcasting) amongst others. When estimating dose, personal characteristics such as body composition should also be taken into account. Table 7.1 provides an overview of factors that we would like to know for individual exposure assessment. To obtain all this data we have various methods at our disposal: a) estimating use of RF-EMF sources by either asking subjects or obtaining data records, b) performing exposure measurements, or c) using models. Each of these categories will be discussed in more detail below.

Table 7.1: Desired input information for RF-EMF exposure assessment.

	Sources	**Position**
Near-field	Personal devices *phone, smartwatch, health sensor*	Relative to the body *Against head, in front of eyes or torso*
Far-field	Broadcasting devices, cell towers *FM radio, WiFi, cellular networks*	Distance to subject's location *Next room, on nearby building*
	Time	**Function**
Near-field	Using the source *Duration, frequency*	Active and passive use *Calling, streaming, background processes*
Far-field	Spent in a location *Duration at location nearby source*	Activity, load *Broadcasting*
	Output	**Personal**
Near-field	Transmission power *Depending on function's information transfer*	Body composition *Age, sex, BMI*
Far-field	Transmission power *Broadcasting*	Body composition *Age, sex, BMI*

Provided sources, positions, and functions are examples and therefore non-exhaustive.

Questionnaires

Recalling information in general can be problematic, especially when asking about events that happened multiple years ago. Recall bias is therefore a potential concern when asking subjects about their use of mobile devices, where there may be over- or underestimation of their actual past use. When investigating health outcomes using a case-control study, there may even be differential recall errors where cases recall differently from controls. In *Chapter 3*, we evaluated these biases within the MOBI-Kids study. Cases with a first primary brain tumour, a potential health outcome of using a mobile phone near the head, were compared with controls. A total of 702 children and young adults (10-24 years old) were asked to recall their mobile phone use (frequency and duration of calls) for multiple months preceding their interview. The results were compared with mobile network operator data records. No indications for differential recall error between cases and controls were found, but both systematic and random non-differential recall errors were observed among both cases and controls. The lack of non-differential recall error is in line with the earlier INTERPHONE study, where recall error amongst adults was studied (1). A trend was observed suggesting an underestimation at low levels of self-reported mobile phone use and overestimation at high levels of mobile phone

7

use for both frequency and duration of calls. The non-differential random errors observed may decrease study power and bias risk estimates towards the null. These results provide valuable input for the MOBI-Kids study and indicate that asking subjects about their mobile phone use, and by extension mobile device use, may not be perfect, but possible as long as calibration is taken into account. Performing this validation study meant that we had to compare subjective questionnaire-based information with an objective "gold standard". While operator data was chosen as the objective measure, it is by no means perfect. There are several issues to consider. The owner of the mobile phone number is not necessarily the main user, something which has to be taken into account during the data collection questionnaire or interview. Billing records only register outgoing calls, as incoming calls are free for the person being called. Using billing records thus misses a large part of the call records. When there are records of both incoming and outgoing calls available, these are not always complete, requiring imputation or exclusion for missing records. Some network operators are able to provide data use records in addition to phone calls. However, that covers only the data sent over cellular networks, not via local WiFi connections. It may be a poor proxy for exposure as the amount of data transferred per month provides no indication for the frequency and duration of data transfer (i.e., was it in short bursts or low but over a longer period of time). Despite these shortcomings, operator data is a method that allows us to collect relatively large amounts of mobile phone use information on many subjects, in some cases even retrospectively, provided that they are consenting to the data collection.

An alternative is the use of software modified phones (SMPs). These are smartphones with a special application (e.g., XMobiSense) installed. The application runs continuously in the background while the phone is in use, collecting device use information. In addition to the number and duration of calls, the laterality (i.e., how is the phone held against the head), hands-free use, data use, and which (cellular) network used are recorded. In *Chapter 4*, we evaluated recall error in mobile phone use, laterality and hands-free use within the MOBI-Kids study. This time only the controls were included, ranging from 10 to 24 years in age. SMPs were used rather than network operator data, with subjects using these as their daily device for four weeks after completing the questionnaires on mobile phone use. Again, both systematic and random recall errors were found, with a similar trend observed as in *Chapter 3* (i.e., underestimation of mobile phone use at lower levels, and overestimation at higher levels of use). The software-modified phones allowed us to collect more data than just frequency

and duration of calls, providing information on laterality and hands-free use. Concerning laterality, we found that young people tend to use their phone frequently on both sides of the head, implying that taking laterality into account when assessing potential brain tumour risks (i.e., the side of the head where the phone is held most frequently is at highest risk) may not be needed and potentially introduce more random noise. This differed from the assumption made in the INTERPHONE study, where 90% of use was assigned to the reported preferred side of use (2).
Recorded hands-free use (i.e., holding phone away from the head while calling) was found to increase with increased self-reported hands-free use. Subjects reporting hands-free device use >50% of call time actually registered only 17% of their call time as such by the software-modified phones. Recall of mobile use of data was found to be poor, indicating that it might be difficult for subjects to accurately recall data use. A subset of participants repeated the questionnaires at 6 and at 18 months. For both number and duration of calls there was a slight drop in recall quality between 0 and 6 months, but little difference between 6 and 18 months. In the LIFEWORK cohort (3) a repeatability of mobile phone use recall was performed as well, finding moderate to high results with a median interval of 151 days between questionnaires. Overall, recall errors appeared to be present not only for the amount of use, but also for the way the mobile phone was used.
With the recall of mobile phone calls and text messages already being difficult for participants, gathering all additional information required in integrative exposure assessment with multiple RF-EMF sources may prove to be even harder. Participants would need to specify the duration of not just phone calls, but also data-based uses such as streaming services and internet browsing. And not just for mobile phones, but for tablets, wearables, and other devices as well. While recall bias has been studied for mobile phones, little is known about other mobile devices. Whether recall quality for these devices is similar, or whether there could be a stacking effect (i.e., asking about many variables at once increasing inaccuracy) when asking for many devices at once, has yet to be determined.
Within the international CREST project, we have attempted a comprehensive survey on mobile device use, the results of which were subsequently used in the integrative model described in *Chapter 5*. Use of a wide variety of modern mobile communication devices was included, ranging from smartphones to smart watches and body-worn sensors (medical sensors). Particularly mobile phone and tablet use were asked in great detail, including which functions were used (amongst others: calling, streaming, browsing), and for each function where the

device was commonly held, how often, and how long it was used in that fashion. This allowed for detailed exposure estimations for different usage scenarios. A total of 1755 adults from four European countries (France, Netherlands, Spain, Switzerland) completed the questionnaire. As there was no gold standard available, the question remains how accurate the participants were able to answer all questions. The average completion time of the survey was well over half an hour, indicating that the use of such a comprehensive list of questions in epidemiological studies may be limited due to significant time investments required from participants.

The abovementioned questionnaires and interviews focus on personal device use, which are generally located within the near-field region (i.e., close to the subject). Sources contributing to far-field exposure, such as mobile phone base stations, FM broadcasting, and personal devices from other people further away are hard to capture by questionnaire. Asking for WiFi networks in a participant's home or place of work can and has been included in questionnaires, but may be of limited information given the ubiquitous nature of WiFi networks. Other methods have to be considered for collecting far-field information. For devices mainly in the near-field (i.e., mostly personal devices) questionnaires can provide a wide variety of information as long as calibrations for recall bias are taken into account.

Exposure monitors

Obtaining information on levels of RF-EMF exposure originating from sources in the far-field region can be achieved by using exposure monitor instead. In *Chapter 2* we performed a series of spot measurements in primary schools in Amsterdam. By setting up an exposure monitor in two classrooms per school we were able to measure RF-EMF levels in 48% of all primary schools in the city. While the large proportion of schools included was a major strength of this study, the spot measurements generally lasted only 14 to 20 minutes, providing limited information on temporal variation. As these measurements took place in 2011 and 2012, a further limitation was that WiFi 5GHz and LTE (Long Term Evolution, 4G networks) were not detected as they were not yet implemented. This limits the applicability of the results to the current situation.

Rather than performing spot measurements, exposure monitors can be provided to study participants to follow their personal RF-EMF exposure levels over multiple days. Within the GERoNiMO project we involved parent-child pairs

in multiple countries (Denmark, Slovenia, Spain, Switzerland, Netherlands), having both the parent and child carry around an exposure monitor for one week (4). In addition to the monitor, both parent and child were requested to keep a location diary and to carry around a GPS tracker. The resulting measurements were combined with location data and split into multiple micro-environments (e.g., at school in a classroom, traveling by train, at home inside), allowing average exposures at those locations to be determined for both the participating individuals and as averages for the study population. As participants were followed for multiple days the micro-environments were measured multiple times per participant, allowing for a better indication of their personal exposure levels compared to only performing brief spot measurements.
Unfortunately, personal exposure monitors come with some limitations. As the device is usually worn around the hip, the measured RF-EMF levels are slightly different from those at the head. The measured exposure levels reflect a whole-body dose rather than a specific anatomical site. Related to the location at the body is the effect of body shielding. The body of the participant carrying the device is shielding part of the RF-EMF exposure, leading to some underestimation of exposure (5). In small scale studies each device could be calibrated to the participant's body, but this is infeasible in a larger study. Here, one generic correction factor for body shielding could be applied to measurements from all participants, though the estimates for what this factor should be vary between studies. Alternatively, sensors integrated in clothing could be used, as developed in the ACCEDERA project where RF-EMF sensors on the front and back of a vest were used to avoid body shielding. Next, there is the issue of cross-talk. The current employed exposure monitor splits its measured RF-EMF levels into multiple frequencies, representing the different cellular networks (e.g., GSM uplink, UMTS downlink, WiFi). When cross-talk occurs, a signal is counted in two different frequency bands. While there are post hoc corrections available, these cannot detect all cross-talk that occurred (6). Lastly, while multiple day personal measurements provide a large amount of information on (far-field) exposure levels, there are limitations to its scalability. It took nearly 1.5 years and an extensive international measurement campaign to obtain measurements of 294 parent-child pairs in the abovementioned study. Where a questionnaire can be quickly collected, RF-EMF exposure monitors are expensive, relatively fragile and require regular calibrations, making it infeasible to measure everyone in a large cohort study. Alternatively, modelling efforts could be considered.

Modelling exposure

While the modelling efforts in this thesis were mainly focused on integrative exposure modelling, it is good to briefly touch on 3D wave propagation models. Rather than providing participants with a personal exposure monitor, antenna data can be used to estimate RF-EMF exposure levels originating from cellular networks at each location. Using the NISMAP model, it is possible to reliably estimate exposure resulting from base stations using antenna positions, transmission power, and building heights (7). Another approach involves the creation of RF-EMF heat maps using kriging (8). Both methods provide maps indicating RF-EMF exposure levels at set locations, covering larger areas compared to measurement campaigns. Moderate correlations have been shown between measured personal and modelled exposure (9). As a person moves throughout the day, their location changes and as a result they are in many different locations for which an estimate was modelled. Combining the modelled RF-EMF heat maps with GPS tracking data could be considered.

Integrative Exposure Model

As mentioned previously, an individual's total RF-EMF dose originates from exposure received from multiple RF-EMF sources in their environment. Up until now we have discussed various methods of gathering information on these sources and their strengths and limitations. Questionnaires can be used to gather information on personal devices in the near-field, which ones are being used, how are they being used, for how long, and at which location relative to the individual's body. Exposure measurements and modelling can provide insights into far-field exposure levels by either carrying an exposure monitor around for a while or modelling RF-EMF levels at locations which the subject frequently visits (e.g., at home, at work, or at school). Ideally, we would like to bring all this information together in a comprehensive individual exposure assessment: one where exposure levels are estimated by taking all RF-EMF sources nearby into account. Individual dose levels can be used for health outcome analyses, while performing a comprehensive assessment for large groups of people enables the creation of population exposure scenarios. These can be used in risk assessment and risk mitigation to see which RF-EMF sources are the relevant contributors (i.e., contribute at least a certain percentage of total daily dose), which are the highest contributors and which ways of using devices are responsible for the highest exposure levels. The results can then be used to formulate technical and non-technical interventions aimed at reducing individual RF-EMF exposure levels (see Box 7.1 for more information).

Box 7.1: Exposure reduction strategies
While no definitive link between RF-EMF exposure and health effects has been shown, public concern around RF-EMF remains. It may therefore be desirable to reduce personal exposure to RF-EMF. But where to start? Many methods have been suggested. Some are effective, such as the removal from all WiFi-routers from a home. Others are not so effective or may even increase exposure, such as the application of an aluminium shield to the back of a smartphone, potentially forcing the device to increase its transmission power to keep a signal.

The results from our Integrated Exposure Model in *Chapter 5* allows us to formulate non-technical interventions aimed at reducing exposure levels. These are generally focused on personal device use, as far-field exposure is generally not controlled by the exposed individual. In general, we have observed higher RF-EMF exposure levels from device functions requiring higher amounts of data, such as streaming services. Below are three examples of non-technical interventions:

- *Disable the use of 2G networks on your smartphone*
  Phone calls on 2G networks produce significantly higher exposure levels to the brain compared to calls made on 3G networks. As modern smartphones allow a preferred network selection, disabling calls over 2G networks is a way to reduce your exposure levels when there is sufficient 3G coverage
- *Only stream videos when your device is on a table*
  Streaming video continuously requires large amounts of data. Moving your phone or tablet further away from your body by placing it on a nearby table reduces your exposure levels
- *Downloading versus streaming*
  Allow your device to download the video in its entirety before viewing, eliminating continuous data downloading during streaming

Our Integrated Exposure Model (IEM includes ten RF-EMF sources (mobile phones, DECT phones, tablets, laptops, body area networks, smartwatches, on/near body devices, virtual reality headsets, WiFi routers, and far-field) and can estimate daily dose for 64 anatomical sites, including the whole body and whole brain. When relating to health outcomes the anatomical site most relevant to the suspected outcome can be chosen rather than relying on a single whole-body estimate. The IEM takes many of the factors complicating RF-EMF exposure assessment identified in *Chapter 1* into account. Distinct functions can be specified for each included source (e.g., streaming on a tablet, being at home for far-field estimates) and a distinct duration and transmission power can be assigned to each function (e.g., on a tablet, streaming video for 25 minutes with 80 mW transmission power). Meanwhile the source position relative to the body as well as body characteristics (i.e., BMI, age, sex) are considered.

In *Chapter 5* the IEM was used to estimate individual RF-EMF dose for 1755 adult participants in four European countries (France, Netherlands, Spain, Switzerland) by combining device use results with exposure monitoring results from the aforementioned CREST mobile device use survey and GERoNiMO parent-child study. The dose estimations were performed for multiple anatomical sites throughout the body, including whole body and whole brain dose, enabling researcher to look at the anatomical site they expect to be most relevant for a particular exposure pattern. The individual dose estimates were subsequently combined into snapshots of population RF-EMF doses in the participating countries. The results indicate an overall higher RF-EMF dose in younger age groups, with near-field sources (i.e., personal devices) driving the differences between groups. Differences between countries were observed, driven by both differing use profiles and differing far-field exposures. Performing mobile phone calls on a 2G network was found to be the main contributor to whole-brain dose. For whole-body dose, far-field and other RF-EMF sources (i.e., tablets, laptops, and WiFi-routers) played a prominent role as well.

The creation of this model was not without difficulties. While gathering the required input information, we ran into issues gathering information on transmission powers associated with various functions of devices. Very little information was available in literature, and in parts we were forced to rely on expert estimations of transmission power. Detailed information on how participants are using their personal devices is of little use without estimates of transmission power associated to quantify levels of exposure. This knowledge gap should be addressed in future studies. Various efforts are currently being considered, including smartphone applications that would be reading the transmission power directly from the phone. For devices that do not have the ability to run such an app (e.g., small sensors, fitness trackers), a measurement campaign could be created where output powers of common device use scenarios are recorded. Still, obtaining reliable output power measurements appears to be a challenging task. Rather than performing surveys and measurement campaigns, manufacturers of mobile communication devices could be required to provide output power estimations for their devices in various scenarios.

While the capabilities of our model are promising, there are many uncertainties involved. Input information (e.g. recall bias, measurement inaccuracies), specific absorption rate (SAR) estimation for the anatomical sites, and lack of output power knowledge combined lead to a large global uncertainty. Still, the IEM is an important tool for estimating both individual and population dose levels in epidemiological studies, aiding in the assessment of population health impact of RF-EMF exposure. With the identification of the main contributing sources it also potentially provides a basis for future exposure reduction strategies. Already the IEM is being used in multiple studies and might prove its utility in the coming years.

Context-sensitive ecological momentary assessments

The previous sections have focused on collecting and analysing data on RF-EMF exposure levels for comparison to health outcomes. Mostly these have been discussed in relation to longer term health outcomes, for example brain tumours. There have however been reports of individuals ascribing acute health problems to exposure to RF-EMF. These include concentration problems, headaches and fatigue, occurring within minutes following exposure (10). These symptoms often have a rapid onset following exposure. When assessing the effects of RF-EMF exposure on these symptoms, as little lag time as possible between an exposure event and symptom onset is desired. Modelling an integrative dose level per day does not provide enough resolution in these cases.

Ecological Momentary Assessments (EMA), a data collection methodology used in, amongst others, clinical psychology, could help in this situation. They involve the repeated collection of data under real-world environment conditions, close in time to an event, at strategically selected moments (11). An extension on this concept are the context-sensitive ecological momentary assessments (CS-EMA), where a data stream is used to trigger assessments when predefined conditions are met. In *Chapter 6* we have applied a CS-EMA based method to evaluate its feasibility in environmental health research, with RF-EMF exposure being used as a test case. Rather than asking subjects for their mobile device use in order to assess RF-EMF exposure levels, a real-time measurement by a personal exposure monitor was analysed continuously by the subject's smartphone. Based on trends in the measurements (e.g., sudden peaks, increasing averages) questions showed up on the subject's smartphone concerning their wellbeing. In the pilot study we collected 34 complete datasets with a question completion rate of 74%, with subjects reporting minimal influence on daily activities.

Where the daily dose estimations of the IEM provide valuable information for

longer term health effects, the CS-EMA method is geared towards short-term effects. Using an exposure monitor bypasses any recall errors on behalf of the subject. It does not exclude previously mentioned issues with measurements such as body shielding or frequency band crosstalk. The method allows for new kinds of research in the RF-EMF field, with the ability to closely look at reports of hypersensitivity to electromagnetic fields. As Martens concludes in her PhD thesis (12), risk appraisal plays an important role in the assignment of symptoms to RF-EMF exposure from mobile phone base stations, but the etiological role is not fully clear. Here the CS-EMA method may help in gaining new insights.
While this thesis is focused on RF-EMF exposure, the CS-EMA approach provides possibilities for broader applications and expansions. There are currently a wide range of real-time sensors available, ranging from RF-EMF exposure monitors and air pollution sensors, to health sensors and activity trackers. Data from these sensors can be streamed directly to centralized servers capable of processing and analysing the data streams. From here, a researcher can change the assessment conditions in real-time based on results collected so far, rather than setting up all parameters at the start of a measurement period only. The creation of an adaptive, dynamic CS-EMA platform capable of interacting with multiple data streams has the potential to further research for not just RF-EMF, but environmental exposures in general. A step in this direction has been made with the MEES project, were sensor data, geospatial data, and information on health and wellbeing are combined into a single platform with both research and public awareness in mind (13).

Outlook

A comprehensive exposure assessment includes all relevant exposure sources. For RF-EMF, the best time for this was 25 years ago. During the era of second generation networks, there were FM broadcasting stations, mobile phone base stations, and DECT and mobile phones being used to make phone calls. These were held near the head when making calls, making the brain the main anatomical site of interest. WiFi and Bluetooth signals, or other devices such as tablets and fitness trackers were not yet in the picture. However, as the Health Council of the Netherlands concludes in her report in 2007 (14), no causal connection was found between adverse health outcomes and exposure to RF-EMF from mobile phones or mobile phone base stations. In the same report it is advised to continue with scientific research on this subject.

A lot has changed since then. Mobile phones are no longer being used just for phone calls. They provide access to the internet, are capable of streaming audio and video, and have become an integral part of our daily lives. They are no longer held solely near the head for making phone calls, but rather in front of the body, in a pocket, or on a nearby table while watching videos, streaming music, or typing messages. Consequently, the brain might no longer be the main anatomical site of interest when it comes to RF-EMF exposure. Meanwhile novel devices have been introduced. From the well-known tablets all the way to fitness trackers and personal health sensors. As all of these devices are communication wirelessly, they are all potentially relevant sources of RF-EMF exposure. Alongside mobile phones the cellular networks have evolved as well, with the fifth generation of networks being deployed at the time of writing. With these rapid changes and increasing diversity of devices, it is becoming more difficult for study participants to accurately report their mobile phone use, let alone to report on the use of all their other mobile devices.

We currently have exposure monitors which can be worn for multiple days to provide insights into (far-field) RF-EMF exposure levels. Alternatively, models using antenna position information can be used to estimate these levels for many locations. With the current tools we have, namely questionnaires, exposure monitors, exposure models, and a comprehensive integrative exposure model like the IEM, we can derive daily RF-EMF exposure levels with reasonable accuracy. That is, for all technologies up until fourth generation networks. As briefly elaborated upon in *Chapter 1*, the new fifth generation networks use new technologies to connect many more devices with high bandwidth, low latency connections. Many of our current tools are not able to account for technologies such as massive MIMO (multiple input and multiple output), directed beamforming, and micro-cellular networks, rendering them largely inadequate for the coming 5G environment.

The question is, what are we going to do tomorrow? Mobile communication technology is developing at an incredibly fast pace, with novel devices and improved communication technologies being released regularly. As of date, the fifth generation networks are being deployed, invalidating in the near future our current models and tools in the near future. In a way, we are continuously one step behind: as soon as we have developed reasonably accurate exposure estimations, newer, more complex technologies appear, changing the playing field. Keeping up will mean significant investment in RF-EMF research over the coming years. Even so, as seen with the integrated exposure model, uncertainty is added with each step. Estimating rapidly fluctuating transmission powers, beam

directions, and other new technological innovation will each add to the overall uncertainty. At some point the uncertainties may become so large that exposure misclassifications prevent an epidemiological study from obtaining sufficient power to result in informative conclusions. While this can be countered by increasing our study sizes, there is a limit to how many participants we can include.
While a lot of research has been performed over the past decades involving the potential health impact of RF-EMF exposure, no conclusive evidence has been found for an adverse relation between exposure levels and health effects such as brain tumours. It could be that there are, in fact, no adverse health effects of exposure to the RF-EMF levels currently in use in society. Yet public concern remains relevant. With the levels of integration of mobile communication technologies in modern society, even a tiny risk at the population level could have a high impact. As RF-EMF is currently on the IARC priority list for evaluation (15) it is important to see whether we can gain more clarity on the issue in the coming years. Research is therefore still needed.
There are other aspects to potential health effects from mobile communication devices besides RF-EMF levels. Extended mobile phone use has a negative effect on sleep quality (16), on stress, and on symptoms of depression (17). When texting while driving, the safety of both drivers and other road users is being compromised (18). Seeing associations between these factors and mobile phone use, should we continue funding towards RF-EMF exposure assessment? Or should we rather investigate screen time, blue light exposure, sleep quality, and mental health concerns related to mobile communication devices in general. It might be more useful to shift our focus to these issues.
In conclusion, rapid technological improvements are forcing continuous updates to RF-EMF exposure assessment. Questions asked in an epidemiological cohort study today may no longer be sufficient in five or ten years, and current exposure models will require frequent updates. RF-EMF exposure assessment will therefore be a highly dynamic subject as long as the current trend of technological innovation continues, as shown by this thesis.

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English summary

Mobile communication devices have become a staple of our everyday lives. From smartphones and tablets to fitness trackers and health sensors, all of these devices use radiofrequency electromagnetic fields (RF-EMF) for communication. Extensive mobile communication networks, ranging from second generation to the recently introduced fifth generation cellular networks, as well as WiFi, Bluetooth and many others communication technologies are in use to support these devices. Consequently, RF-EMF exposure has become nearly continuous. With the rise in use of RF-EMF came concern about related potential adverse health effects. To address these concerns an accurate and biologically relevant exposure assessment is required. This is no easy task, as there are many factors influencing RF-EMF exposure levels.

RF-EMF sources can be divided into those nearby an individual (near-field) and further away (far-field). Beginning with the near-field, ideally all devices using RF-EMF are included in the assessment. For each device we would need to know a) the frequency and duration of use, b) functions used (e.g., calling, streaming), c) amount of data transfer needed for each function, d) where it is located relative to the body, and e) which communication network is used. For far-field sources, such as mobile phone base stations, radio broadcasting towers, and WiFi networks, we would like to the strength of the source and the location of the individual relative to the source. In addition, there are personal characteristics determining exposure levels: age, sex, BMI, amount of adipose tissue all influence levels at an anatomical site of interest (e.g., the brain).

The above information can be collected by asking individuals about their mobile device use via questionnaires or interviews, by using exposure measurement devices, or by modelling exposure levels. With each method having its own strengths and limitations. Once the information is available, the next step is integrating the exposure levels of all individual sources into a single dose estimate. For individual exposure assessment in epidemiological studies, we can compare this combined those with potential health outcomes. The aim of this thesis was to highlight the challenges of RF-EMF exposure assessment by exploring some of the above-mentioned data collection methods. Following this, a novel method of integrative individual exposure assessment was designed. In addition, a method for assessing short-term health outcomes of RF-EMF was developed.

We first examined the use of exposure measurement devices in 102 primary schools in Amsterdam, the Netherlands. Spot measurements, averaging only 14-20 minutes, were taken in two classrooms of nearly all schools between July 2011 and July 2012, covering 48% of all primary schools in the city. An average power density of 70.5 μW m^{-2} (0.16 V m^{-1}) was found, with the frequency bands "mobile phone downlink" and "DECT" (Digital Enhanced Cordless Telecommunications) contributing most to overall exposure. Overall these levels were low, with high variability in the relative contributions of different frequency bands to the overall power density. While the large amount of schools included was a major strength of this endeavour, the brief duration provided only limited information on temporal variation. In addition, the measurements being performed in 2011 and 2012 meant that no information on modern WiFi 5GHz and LTE (Long Term Evolution, 4G networks) was collected as these technologies were not common yet. An indication of the rapid growth of mobile communication technology and something that has to be taken into account while interpreting RF-EMF exposure assessments.

When asking subjects about their mobile device use history, recall bias comes into play. It consists of systematic and random errors which occur when mobile device use is recalled incorrectly, leading to under- or overestimations of device use. Even worse, within a case-control the cases could recall their use differently than the controls, leading to differential recall bias. Within the MOBI-Kids study (a study on potential effects of childhood and adolescent exposure to EMF from mobile phones) we performed a retrospective validation study assessing patterns in recall and differences between cases and controls. For 702 children and young adults (10-24 years old) we compared self-reported mobile phone use to phone records from mobile phone network operators, allowing for a recall period of up to two years. There was no indication for differential recall error. However, we did observe non-differential systematic and random errors, with underestimation of the number of calls and overestimation of the call duration. These could bias risk estimates and reduce the overall power of studies.

The aforementioned validation study used network operator data as a "gold" standard. In reality, these records are often incomplete. In the MOBI-EXPO validation study, part of the larger MOBI-Kids study we compared mobile phone use recall to software modified phones (SMPs). These phones ran an application recording calls, text messages, and data usage. For each call the laterality (i.e., how is the phone held against the head), hands-free usage, and the type of network used was also recorded. For 466 participants, again aged 10-24 years old, it was found that young people can recall phone use moderately well. Recall was dependent on the amount of phone use, where participants with low mobile phone use underestimated their use and participants with high mobile phone use overestimating their use. These findings were in line with the aforementioned validation study using mobile phone network operator data. Likewise, both systematic and random recall errors were observed.

We developed a comprehensive RF-EMF dose estimation tool in the form of the Integrated Exposure Model (IEM), taking input information from both questionnaires, exposure measurements and models in order to estimate individual RF-EMF doses. The model included ten RF-EMF sources in both the near-field and far-field, covering an important part of the RF-EMF sources in use today. Dose estimations were available for 64 different anatomical sites, including the whole body and the whole brain. Not only was the total dose estimated, the model also showed the contribution of individual sources to the total dose. Individual exposure levels were estimated for 1755 adult participants across four European countries. Taking the individual estimates to form a population snapshot, median whole-body and whole-brain doses of 183.7 mJ/kg/day and 204.4 mJ/kg/day respectively were found. Mobile phone calls near the head using 2G networks were the main contributors for whole-brain dose. For the whole-body far-field of telecommunications and multiple other RF-EMF sources played a prominent role as well. The results can be used as input for exposure reduction strategies aimed at lowering RF-EMF levels, with the modular structure of the IEM allowing inclusion of new technologies in the future.

There have been reports by individuals attributing RF-EMF exposure to acute health effects (e.g., headache, concentration loss, fatigue). These symptoms often have a rapid onset time following exposure. We have developed a platform based on the context-sensitive ecological momentary assessment (CS-EMA) methodology, where a continuous data stream from an RF-EMF exposure monitor was continuously processed by a smartphone application. The smartphone would then display questions concerning wellbeing and health once predefined triggers were met (e.g., sudden peaks in exposure levels). In a pilot study we assessed the questionnaire completion rate, obtaining 34 complete datasets with a question completion rate of 74%. The method allows for a new way of assessing RF-EMF related health outcomes as well as health outcomes related

other environmental exposures by using various data streams.
Overall various challenges involving RF-EMF exposure assessment were highlighted. With the rapid ongoing technological improvements continuous updates to our assessment methodologies are required. Meanwhile, global uncertainty in our assessments is increasing with more and more factors that need to be estimated. The question remains whether these will result in exposure misclassifications so large that, if there are actual adverse health outcomes related to RF-EMF exposure, we are unable to detect them. Scientific research so far has provided no conclusive evidence that these adverse outcomes exist, even with older wireless technologies where exposure was higher and could be better characterised. On the other hand, other aspects of mobile device use are showing associations with adverse health outcomes: decreased sleep quality, stress, and decreased mental health symptoms. A shift in research focus from RF-EMF exposure towards these factors may be more beneficial for overall public health.

Nederlandse samenvatting

Mobiele apparaten zijn niet meer weg te denken uit ons dagelijks leven. Van smartphones tot smartwatches, ze gebruiken allemaal radiofrequente elektromagnetische velden (RF-EMV) om te communiceren. Wijdverspreide mobiele communicatienetwerken, van 2G tot 5G, maar ook WiFi, Bluetooth en vele andere protocollen worden gebruikt om onze mobiele apparaten van informatie te voorzien. Het gevolg hiervan is dat we vrijwel ononderbroken aan RF-EMV worden blootgesteld. Er zijn dan ook zorgen geuit over de mogelijke gezondheidseffecten die deze blootstelling zou kunnen veroorzaken. Om deze zorgen te adresseren, is een accurate en biologisch relevante blootstellingsbeoordeling nodig. Dit is geen gemakkelijke taak, gelet op de vele factoren die RF-EMV-blootstelling beïnvloeden.

RF-EMV-bronnen kunnen opgedeeld worden in bronnen die dichtbij (near-field) en verder weg (far-field) zijn. Voor de near-field bronnen (vaak persoonlijke mobiele apparaten) willen we weten [a] hoe vaak en hoe lang ze gebruikt zijn, [b] waarvoor (bijv. bellen, browsen), [c] de hoeveelheid verzonden data per gebruik, [d] de locatie ten opzichte van het lichaam en [e] het gebruikte communicatienetwerk. Voor far-field bronnen (bijv. zendmasten, WiFi-netwerken) willen we de sterkte van de zender weten en de locatie van de zender ten opzichte van de persoon wiens blootstelling onderzocht wordt. Daarnaast willen we een aantal persoonlijke eigenschappen weten: leeftijd, geslacht, BMI en hoeveelheid vetweefsel. Dit zijn factoren die de hoeveelheid RF-EMV beïnvloeden die uiteindelijk aankomt op een anatomische locatie (bijv. de hersenen).

De bovenstaande informatie kan verzameld worden met behulp van vragenlijsten over gebruik van mobiele apparaten, door een blootstellingsmeter in te zetten, of door blootstellingsniveaus te modelleren. Elke methode heeft voor- en nadelen. Wanneer alle benodigde informatie is verzameld, kan de volgende stap gezet worden: een integratieve blootstellingsbeoordeling waarbij blootstelling van meerdere losse RF-EMV-bronnen samengevoegd wordt tot één enkele dosis die de totale RF-EMV-blootstelling van een individu omvat. In epidemiologische studies kunnen deze individuele blootstellingsbeoordelingen gekoppeld worden aan potentiële gezondheidseffecten. Dit proefschrift had als doel de uitdagingen van RF-EMV-blootstellingsbeoordeling te benadrukken door de eerdergenoemde methoden van dataverzameling nader te bekijken. Met de resultaten is een nieuw integratief blootstellingsbeoordelingsmodel ontworpen. Daarnaast is een methode ontwikkeld waarmee acute potentiële gezondheidseffecten onderzocht kunnen worden.

Allereerst hebben we het gebruik van blootstellingsmeters onderzocht in 102 basisscholen in Amsterdam (Nederland). Er zijn puntmetingen uitgevoerd, waarbij één locatie 14-20 minuten werd bemeten, tussen juli 2011 en juli 2012 in twee klaslokalen van vrijwel iedere school. 48% van alle basisscholen in Amsterdam zijn meegenomen in deze metingen. De gevonden vermogensdichtheid was gemiddeld 70,5 μW m^{-2} (0,16 V m^{-1}), waarbij de frequentiebanden “mobiele telefoon downlink” en “DECT” (Digital Enhanced Cordless Telecommunications) de grootste bijdrage leverden aan de totale blootstelling. De gevonden waarden waren over het algemeen genomen laag, met hoge variabiliteit in de relatieve bijdrage van de verschillende frequentiebanden aan de totale vermogensdichtheid. Hoewel de grote hoeveelheid bemeten scholen een duidelijk sterk punt waren van deze studie, zorgde de korte tijdsduur van de puntmetingen voor een beperkte hoeveelheid beschikbare informatie in de tijd. Doordat de metingen in 2011 en 2012 zijn uitgevoerd was er geen informatie beschikbaar over moderne 5GHz WiFi-netwerken en LTE (Long Term Evolution, 4G netwerken) aangezien deze technieken nog niet algemeen gebruikt waren destijds. Dit illustreert de snelle groei van mobiele communicatietechnologie en is iets waar rekening mee gehouden moet worden bij het interpreteren van RF-EMV-blootstellingsbeoordelingen.

Herinneringsbias speelt een rol in het navragen van de gebruikshistorie van mobiele apparaten. Het omvat zowel systematische als toevallige fouten welke voorkomen wanneer de gebruikshistorie foutief herinnerd wordt, wat leidt tot een onder- of overschatting van de daadwerkelijke gebruikshistorie. In een patiënt-controleonderzoek kan bovendien differentiële herinneringsbias optreden, waarbij patiënten een andere bias hebben dan de controlegroep. In de MOBI-Kids studie hebben we een retrospectieve validatiestudie uitgevoerd om patronen en verschillen in herinnering tussen patiënten en controles te onderzoeken. We vergeleken zelfgerapporteerde gebruikshistorie van mobiele telefoongebruik met gegevens van mobiele netwerk operatoren voor 702 kinderen en jongvolwassenen (10-24 jaar). Voor een aantal deelnemers waren

gegevens tot twee jaar terug beschikbaar. Er was geen indicatie voor differentiële herinneringsbias, maar er zijn wel systematische en toevallige fouten geobserveerd. Het aantal telefoongesprekken werd onderschat, terwijl de totale duur van telefoongesprekken overschat werd. Dit kan risicoschattingen beïnvloeden en het onderscheidend vermogen van studies verlagen.
Gegevens van mobiele netwerk operatoren zijn als gouden standaard gebruikt in de bovengenoemde validatiestudie. In werkelijkheid zijn deze gegevens echter vaak incompleet. In de MOBI-EXPO-validatiestudie, onderdeel van de grotere MOBI-Kids studie, zijn daarom softwarematig aangepaste telefoons (SMPs) gebruikt. Op deze telefoons is een applicatie geïnstalleerd die de aantallen en duur van telefoongesprekken, tekstberichten, en datagebruik registreert. Voor ieder telefoongesprek worden lateraliteit (hoe wordt de telefoon tegen het hoofd gehouden), handenvrij gebruik, en het type netwerk geregistreerd. Voor 466 deelnemers, 10-24 jaar oud, werd gevonden dat adolescenten en jongvolwassenen zich hun gebruikshistorie redelijk kunnen herinneren. De kwaliteit van de herinnering was afhankelijk van hoe vaak de telefoon werd gebruikt. Deelnemers met een laag gebruik onderschatten hun eigen gebruik en deelnemers met een hoog verbruik overschatten dit. Deze bevindingen zijn in lijn met de eerdergenoemde validatiestudie waarin data van mobiele netwerk operatoren werd gebruikt. Ook hier zijn zowel systematische als toevallige fouten gevonden.
We hebben een uitgebreid RF-EMV-dosisschattingsmodel ontwikkeld in de vorm van het Integrated Exposure Model (IEM), waarbij gegevens van zowel vragenlijsten, blootstellingsmeters als modellen worden gebruikt om individuele RF-EMV doses te schatten. Het model omvat tien verschillende RF-EMV-bronnen in zowel het near-field als het far-field en kan schattingen geven voor 64 anatomische locaties, waaronder het gehele lichaam en de gehele hersenen. Het model schat niet alleen de totale dosis, maar het geeft ook weer welke bijdrage de verschillende bronnen aan de totale dosis geven. Dankzij de modulaire opbouw van het model kunnen nieuwe technologieën in de toekomst geïncludeerd worden. Voor 1755 volwassenen uit vier verschillende Europese landen werden individuele blootstellingsniveaus geschat. Deze schattingen werden gebruikt om een momentopname van de populatieblootstelling te vormen, waarbij een mediane dosis van 183,7 mJ/kg/dag en 204,4 mJ/kg/dag werden gevonden voor respectievelijk het hele lichaam en de hersenen. Gesprekken met mobiele telefoons over 2G netwerken waren verantwoordelijk voor het leeuwendeel van de blootstelling aan de hersenen. Voor de blootstelling aan het hele lichaam speelden far-field bronnen en diverse near-field bronnen eveneens een belangrijke rol. De resultaten kunnen gebruikt worden voor het ontwikkelen van strategieën om

blootstelling te verlagen.
Er zijn meldingen geweest waarbij individuen acute gezondheidseffecten (bijv. hoofdpijn, concentratieverlies) toeschrijven aan RF-EMV-blootstelling. De gemelde effecten komen vaak snel op na een blootstelling. We hebben een methode ontwikkeld waarbij een constante stroom van gegevens van een blootstellingsmeter continu verwerkt wordt door een smartphone applicatie. Indien aan bepaalde, vooraf ingestelde, voorwaarden werd voldaan (bijv. plotselinge piek in RF-EMV-blootstelling) stelde de applicatie vragen gerelateerd aan het welzijn en de gezondheid van de deelnemende proefpersoon. Deze methode is gebaseerd op zogeheten context-sensitive ecological momentary assessments (CS-EMA), oftewel kortstondige momentane beoordeling gebaseerd op contextuele factoren (de blootstellingsmeter). De hoeveelheid ingevulde vragenlijsten is in een pilotstudie onderzocht, waar in 34 complete datasets 74% van de vragenlijsten werd voltooid. Nieuwe manieren om RF-EMV gerelateerde gezondheidseffecten, maar ook van andere omgevingsfactoren, te onderzoeken worden mogelijk gemaakt dankzij deze methode.
In dit proefschrift zijn diverse uitdagingen die komen kijken bij de blootstellingsbeoordeling van radiofrequente elektromagnetische velden nader bekeken. De doorlopende technische ontwikkelingen en innovaties zorgen ervoor dat we onze beoordelingsmethoden constant moeten verbeteren en vernieuwen. Tegelijkertijd worden de diverse onzekerheden in onze methoden steeds groter doordat er meer en meer factoren meegenomen moeten worden. Daardoor blijft de vraag of deze onzekerheden de blootstellingsmisclassificaties zodanig groot maken dat we potentiële gezondheidseffecten van RF-EMV-blootstelling niet meer kunnen detecteren. Wetenschappelijk onderzoek tot nu toe heeft nog geen sluitend bewijs gevonden dat deze gezondheidseffecten bestaan, zelfs in tijden dat oudere draadloze technieken gebruikt werden die door hun hogere RF-EMV-blootstelling beter gekarakteriseerd konden worden. Daar staat tegenover dat andere aspecten van mobiele apparaten geassocieerd worden met gezondheidseffecten als verminderde slaapkwaliteit, stress, en verminderde geestelijke gezondheid. Door de focus te verschuiven van RF-EMV-blootstelling naar deze aspecten kan mogelijk een grotere bijdrage geleverd worden aan de verbetering van de publieke gezondheid.

List of publications

This thesis

van Wel L, Liorni I, Huss A, Thielens A, Wiart J, Joseph W, Capstick M, Cardis E, Vermeulen R. *Organ-specific integrative exposure assessment: Radio-frequency electromagnetic field exposure and contribution of sources in the general population.* Manuscript being prepared for submission

van Wel L, Huss A, Kromhout H, Momoli F, Krewski D, Langer EC, Castaño-Vinyals G, Kundi M, Maule M, Miligi L, Sadetzki S, Albert A, Alguacil J, Aragones N, Badia F, Bruchim R, Goedhart G, de Llobet P, Kiyohara K, Kojimahara N, Lacour B, Morales-Suarez-Varela M, Radon K, Remen T, Weinmann T, Vrijheid M, Cardis E, Vermeulen R. *Validation of mobile phone use recall in the multinational MOBI-Kids study.* Manuscript being prepared for submission

Goedhart G, **van Wel L**, Langer CE, de Llobet Viladoms P, Wiart J, Hours M, Kromhout H, Benke G, Bouka E, Bruchim R, Choi K-H, Eng A, Ha M, Huss A, Kiyohara K, Kojimahara N, Krewski D, Lacour B, 't Mannetje A, Maule M, Migliore E, Mohipp C, Momoli F, Petridou ET, Radon K, Remen T, Sadetzki S, Sim M, Weinmann T, Cardis E, Vrijheid M, Vermeulen R. *Recall of mobile phone usage and laterality in young people: The multinational Mobi-Expo study.* Environmental Research 2018

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Eeftens M, Struchen B, Birks LE, Cardis E, Estarlich M, Fernandez MF, Gajšek P, Gallastegi M, Huss A, Kheifets L, Meder IK, Olsen J, Torrent M, Trcek T, Valic B, Vermeulen R, Vrijheid M, **van Wel L**, Guxens M, Roosli M. *Personal exposure to radio-frequency electromagnetic fields in Europe: Is there a generation gap?* Environment International 2018

Birks LE, Struchen B, Eeftens M, **van Wel L**, Huss A, Gajšek P, Kheifets L, Gallastegi M, Dalmau-Bueno A, Estarlich M, Fernandez MF, Meder IK, Ferrero A, Jiménez-Zabala A, Torrent M, Vrijkotte T, Cardis E, Olsen J, Valič B, Vermeulen R, Vrijheid M, Röösli M, Guxens M. *Spatial and temporal variability of personal environmental exposure to radio frequency electromagnetic fields in children in Europe.* Environment International 2018

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Liorni I, Thielens A, Wiart J, Joseph W, **van Wel L**, Cardis E, Vermeulen R, Capstick M. *Specific absorption rate transfer approximations for integrative radiofrequency exposure assessment in epidemiological studies.* Manuscript submitted

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Cabré-Riera A, El Marroun H, Muetzel R, **van Wel L**, Liorni I, Birks LE, Pierotti L, Wiart J, Joseph W, Thielens A, Huss A, Röösli M, Capstick M, Vermeulen R, Cardis E, Vrijheid M, Hillegers M, White T, Tiemeier H, Guxens M. *Radiofrequency electromagnetic fields exposure, screen time, brain morphology, and attention problems in school-age children.* Manuscript being prepared for submission

Dankwoord

Het is een regenachtige vrijdagavond in oktober, drie maanden voordat ik dit proefschrift in het openbaar verdedig. Hoog tijd om dit laatste en misschien wel meest gelezen hoofdstuk te schrijven.
Dit promotietraject begon ruim vijf jaar geleden, mei 2014, met een mailtje van Roel. Op dat moment was ik al enkele malen op gesprek geweest voor een promotieplaats, zonder succes. Ditmaal vroegen Roel en Hans zich af waarom ik niet had gereageerd op een openstaande vacature. Na enkele gesprekken (waaronder eentje over Skype met Hans in de VS en Roel in China) waren we eruit: ik mocht mijn promotietraject in augustus 2014 starten. Of zoals Ingrid het zei op mijn eerste werkdag: "het is je dan uiteindelijk toch gelukt!"
Wat volgden waren vijf veelbewogen jaren (Figuur 1). Ik dook in de wondere wereld van radiofrequente elektromagnetische velden. Eerst binnen het Europese project GERoNiMO, maar al snel kwamen daar meerdere (inter)nationale projecten bij. Ik heb veel geleerd, gereisd, leuke collega's ontmoet en nieuwe vrienden gemaakt. Het is dan wel mijn naam die op de kaft staat, het had er nooit gelegen zonder de hulp en steun van velen.
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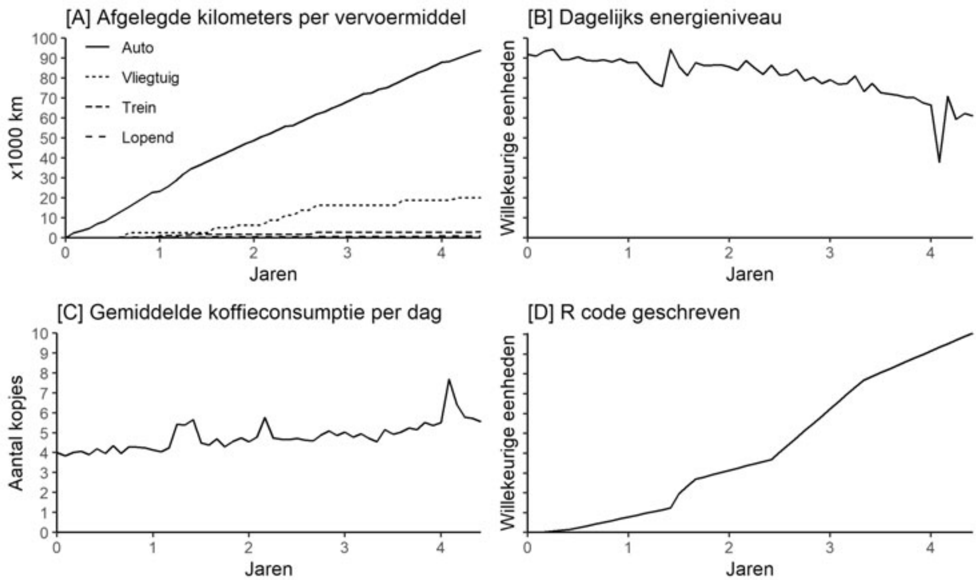

Figuur 1: Voortgang van mijn promotietraject, weergegeven in [A] kilometers, [B] dagelijkse energie, [C] IRAS koffiebekertjes en [D] R code. Niet gecorrigeerd voor mogelijk beïnvloedende factoren als veldwerk, bezoekjes aan Barcelona of pasgeboren babies.

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Curriculum Vitae

Luuk van Wel was born in West Maas en Waal, the Netherlands, on September 1st, 1988. From 2000 to 2006 he attended secondary school at Pax Christi College in Druten with a study program focused on subjects in nature and health. Luuk became interested in the effects of environmental and pathological factors on health and proceeded to study Biomedical Sciences at Radboud University Nijmegen. After receiving his BSc degree in 2009, he continued with his MSc degree in Biomedical Sciences with a focus on occupational and environmental exposure and risk assessment. Following multiple internships, at Public Health Services (GGD) Gelderland-Midden and the Radboud University Medical Centre (Radboudumc), he graduated Bene Meritum in 2012. After his graduation, he worked in various roles for the department of Hematology of the Radboudumc, before starting as a junior researcher at the department of Health Evidence at the same institute. From 2014 to 2018 Luuk worked on his PhD at the Institute for Risk Assessment Sciences (IRAS) at Utrecht University, the results of which are described in this thesis. Since January 2019 Luuk is employed as scientist innovator at the Netherlands Organisation for Applied Scientific Research (TNO).

Institute for Risk Assessment Sciences, Utrecht University