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Modelling of daily radiofrequency electromagnetic field dose for a prospective adolescent cohort

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ABSTRACT

Introduction: Radiofrequency electromagnetic fields originate from a variety of wireless communication sources operating near and far from the body, making it challenging to quantify daily absorbed dose. In the framework of the prospective cohort SCAMP (Study of Cognition, Adolescents and Mobile Phones), we aimed to characterize RF-EMF dose over a 2-year period.

Methods: The SCAMP cohort included 6605 children from greater London, UK at baseline (age 12.1 years; 2014–2016) and 5194 at follow-up (age 14.2; 2016–2018). We estimated the daily dose of RF-EMF to eight tissues including the whole body and whole brain, using dosimetric algorithms for the specific absorption rate transfer into the body. We considered RF-EMF dose from 12 common usage scenarios such as mobile phone calls or data transmission. We evaluated the association between sociodemographic factors (gender, ethnicity, phone ownership and socio-economic status), and the dose change between baseline and follow-up.

Results: Whole body dose was estimated at an average of 170 mJ/kg/day at baseline and 178 mJ/kg/day at follow-up. Among the eight tissues considered, the right temporal lobe received the highest daily dose (baseline 1150 mJ/kg/day, follow-up 1520 mJ/kg/day). Estimated daily dose [mJ/kg/day] increased between baseline and follow-up for head and brain related tissues, but remained stable for the whole body and heart. Doses estimated at baseline and follow-up showed low correlation among the 3384 children who completed both assessments. Asian ethnicity (compared to white) and owning a bar phone or no phone (as opposed to a smartphone) were associated with lower estimated whole-body and whole-brain RF-EMF dose, while black ethnicity, a moderate/low socio-economic status (compared to high), and increasing age (at baseline) were associated with higher estimated RF-EMF dose.

Abbreviations: ANOVA, Analysis of variance; DECT, Digital Enhanced Cordless Telecommunications; IEM, Integrated Exposure Model; RF-EMF, radio-frequency electromagnetic fields; SAR, Specific Absorbtion Rate; SCAMP, Study of Cognition, Adolescents and Mobile Phones; SES, Socio-economic status; UMTS, Universal Mobile Telecommunication System; VoLTE, Voice over LTE (Long-Term Evolution).

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Conclusion: This study describes the first longitudinal exposure assessment for children in a critical period of development. Dose estimations will be used in further epidemiological analyses for the SCAMP study.

1. Introduction

Generation Z, typically defined as those born between 1997 and 2010, is growing up surrounded by mobile communication technologies. They use mobile phones, tablets and laptops both in their education and during leisure time, and this has impacted their lives in many ways. Concern about exposure to radiofrequency electromagnetic fields (RF-EMF) is largely focused on this age group because 1) their brain is still developing (Kheifets, 2005; Feychting, 2005); 2) they are and will be using these devices a lot into the future (Sudan, 2016) and will thus have a high lifetime cumulative exposure compared to previous generations; and 3) their brain typically experiences higher exposures than adults under the same exposure conditions because of skull morphology (Christ, 2010). Children, adolescents and young adults have therefore been targeted as the study population of several major research projects on exposure measurements.

So far, findings from previous studies regarding the relationship between RF-EMF exposure and cognitive function (in children and adults) have been inconsistent (Thomas, 2010; Birks, 2018; Cabré-Riera, 2021; Ishihara, 2020; Foerster, 2018). Most previous research is cross-sectional and thus the possibility of reverse causality remains: is the change in cognitive performance a result of exposure, or the other way around? It is also difficult to disentangle any health effects caused by RF-EMF of wireless communication devices from other consequences of device use, such as sleep displacement (Foerster, 2019; Mireku, 2019), reduced physical activity (Pereira, 2020) and cognitive training (Chetty-Mhlanga, 2020). Therefore, a better understanding of RF exposure and e-media use is necessary for understanding health effects, particularly in children and adolescents.

The SCAMP cohort (Study of Cognition, Adolescents and Mobile Phones) is a prospective cohort study in 6905 adolescents from greater London, UK, which investigates the cognitive and behavioural outcomes of the use of mobile communication technologies (Toledano, 2019). SCAMP specifically aims to disentangle to what extent any associations are due to RF-EMF emitted by mobile phones specifically, by the totality of RF-EMF exposures incurred from communication devices, or due to behavioural and usage related reasons (irrespective of RF-EMF exposure) (Toledano, 2019). Thus, adequate characterisation of RF-EMF exposure is a key aspect of this study.

While personal measurements of RF-EMF give a quantitative and relatively complete, but short-term indication of the exposure (Eeftens, 2018; Jalilian, 2019), they are short-term assessments only and are not a practicable solution for larger groups. Such measurements are appropriate to quantify electric fields for quasi-homogeneous RF-EMF from sources operating far from the body (i.e. RF-EMF exposure from environmental sources such as mobile phone base stations or WiFi access points) but do not adequately take into account RF-EMF arising from personal usage of devices operating close to the body, which has been shown to account for the major part of RF-EMF exposure (Roser, 2015; van Wel, 2021). For these so-called near-field sources, dosimetric approaches are needed to quantify the specific absorption rate (SAR in W/kg tissue weight) by considering the coupling between transmitter and the body.

A combined metric for the RF-EMF dose from near and far-field sources, defined as the cumulative SAR (in J/kg/day) was first introduced as part of two Swiss studies (Roser, 2015; Lauer, 2013), and was further developed within the GERoNiMo study (Generalised EMF Research using Novel Methods – an integrated approach: from research to risk assessment and support to risk management) (van Wel, 2021; Liorni, 2020) and applied by more recent studies (Cabré-Riera, 2021; Foerster, 2018; Cabré-Riera, 2020). This RF-EMF dose model combines dose contributions from both near-field and far-field sources based on specific transfer algorithms (Liorni, 2020), and considers body characteristics as well as typical common usage scenarios, which might affect the position of the source in relation to the body (e.g. making a phone call with the phone next to the head versus in hands-free mode) (van Wel, 2021).

The objective of this study is to apply the RF-EMF dose model within the SCAMP cohort to specific tissues and the whole body at two different time points at baseline (age of children approximately 12 years), and at follow-up (around age 14 years). The results of the dose modelling are described according to the relevance of various contributors to different tissues and organs, the longitudinal development of the estimated dose between baseline and follow-up, and by phone ownership and socio-demographic factors (sex, socio-economic status, ethnicity, age).

2. Methods

2.1. Study population, sociodemographic factors

The SCAMP study approached secondary schools across greater London, of which 39 schools finally took part in the study (Toledano, 2019). Baseline data collection was conducted in Year 7 between November 2014 and July 2016 and the follow up was conducted approximately two years later, in Year 9/10. Extensive public engagement and involvement work was conducted to minimize attrition, specifically for traditionally underrepresented groups (Bruton, 2020). During the same periods as the baseline and follow-up school assessments, a subset of the children from 12 out of 39 schools additionally took part in the "Bio-Zone" assessments (Toledano, 2019; Shen, 2021): face-to-face individual examinations by cohort staff (non-invasive biological samples and anthropometric measurements). Table 1 lists the data derived from each of the five specific assessments relevant for the RF-EMF dose modelling specifically.

2.2. Integrated exposure model estimating daily RF dose

We used the "Integrated Exposure Model" (IEM) dose model, published by van Wel et al. (van Wel, 2021) and Liorni et al. (Liorni, 2020), to estimate daily RF-EMF dose in millijoules per kilogram per day (mJ/kg/day). The IEM was designed to include a diversity of current and near-future sources of RF-EMF (van Wel, 2021), based on specific absorption rate transfer algorithms (SAR) developed by Liorni et al. (Liorni, 2020). Personal exposure to individual sources of RF-EMF may be quantified by the absorbed power averaged over a certain mass or volume, using the specific absorption rate (SAR). The SAR depends on characteristics of persons and tissues, and properties of the RF-EMF source, which are both considered by the transfer algorithm. The IEM estimates the integrated daily dose for to 64 different anatomical sites (hereafter called "tissues"), including the whole body, different organs (e.g. brain, heart), as well as specific brain regions. We present here the results for eight of 64 tissues, relevant for the SCAMP study context: the temporal lobes (left and right), the midbrain, heart, the right and left brain halves, the whole brain and the whole body. This model requires several different inputs: personal information, use scenarios, technical settings of the devices, and far-field contributions from environmental sources.

Table 1
Data relevant to the dose modeling as captured at each assessment.

	Assessment	Location of assessment	Median age at assessment	Main information relevant to dose modeling	N
A1	Baseline school assessment (November 2014 – July 2016)	School	12.1 years (IQR: 11.8–12.3)	*Electronic device use*: mobile phone, cordless phone, cordless phone, laptop, tablet, game console, and internet use both at school and at home. *Anthropometric information*: height, weight, sex, handedness *Demographics*: socio-economic status (parental education, profession) *Environmental*: duration and mode of travelling to school	6605
A2	Follow-up school assessment (November 2016 – July 2018)	School	14.3 years (IQR: 13.9–14.6)	*Electronic device use*: mobile phone, cordless phone, cordless phone, laptop, tablet, game console, and internet use both at school and at home. *Anthropometric information*: height, weight, sex, handedness *Demographics*: socio-economic status (parental education, profession) *Environmental*: duration and mode of travelling to school	5194
A3	Baseline biological samples collection (SCAMP “Bio-Zone”; March 2015 – July 2016) [a]	School	12.4 years (IQR: 12.1–12.6)	*Anthropometric measurements*: height, weight, sex.	1705
A4	Follow-up biological samples collection (SCAMP “Bio-Zone”; November 2016 – July 2018) [a]	School	14.4 years (IQR: 14.0–14.6)	*Anthropometric measurements*: height, weight, sex.	1338
A5	Parental online home questionnaire (November 2014 – October 2018)	Home	12.1 years (IQR: 11.8–12.4)	*Electronic device use*: mobile phone ownership, internet use, WiFi availability, cordless phone and the location of its base station *Anthropometric information*: height, weight *Demographics*: socio-economic status (education, profession)	772

[a] Only 2270 children from 12 out of 39 schools were invited to this supplementary assessment (Toledano, 2019; Shen, 2021).

2.3. Personal information

For our estimates, we considered the following personal information. Sex, age, height and weight of the child is an input to determine the body type used in the transfer function of the model and to estimate the weight of the various organs and tissues for which predictions are being made. These data were typically available from assessments, A3 and A4 (see Table 1). If missing, we filled these in with data from assessments A1 and A2, and lastly from A5 (see Online Supplement Table 1). Questionnaires A1 and A2 included a question about handedness (whether the child was left- or right-handed). We assumed that they held their phone in their dominant hand 80% of the time, and in their non-dominant hand 20% of the time (Langer, 2017). For children who did not indicate a preference, we assumed they used their phone 50% for each side. The dose model further required the input whether the main mobile phone of each subject was a smartphone or a bar/flip phone. Phone ownership was assessed at both A1 and A2, whether the children owned a phone and whether or not this was a smartphone.

2.4. Use scenarios

Use scenarios (hereafter called “scenarios”) refers to the use of different devices (e.g. phones, tablets, laptops) in different positions (e.g. held next to the head, on the lap) during different exposure situations related to the use-specific to activity (e.g. a video call on WiFi or a mobile network call on the UMTS network). Children were asked via questionnaire to estimate the duration of mobile device use when children were in Year 7 (see Table 1: A1) and in Years 9–10 (see Table 1: A2).

Out of 28 scenarios defined in the dose model, we used 12 scenarios, compatible with the data available from the questionnaires. Briefly, the RF-EMF dose model required an estimate of the duration of the activities: 1 mobile phone calls near the head on the 2G network; 2) mobile phone calles near the head on the 3G/4G network; 3) use of a DECT phone near the head; 4) phone calls while wearing a headset; 5) phone data use; 6) phone use in front of the eyes (e.g. video calls while holding the phone when watching the screen); 7) phone use in hands-free mode (e.g. video calls while the phone is on a horizontal surface in front); 8) laptop use; 9) exposure from the phone in standby mode while it is worn on the body (e.g. in pocket); 10) tablet use; and 11) exposure from WiFi routers; 12) far field exposure. Each of these scenarios further required the specification of a power output for the device used in the scenario in that specific position. These values were adopted from previous applications of this model (van Wel, 2021; Cabré-Riera, 2020; Birks, 2021).

2.5. Technical settings related to scenarios

Several technical settings describe the behaviour of the mobile phone in the network such as proportion of 2G and 3G calls or the frequency band for transmission. These were not assessed at an individual level and were therefore chosen to be the same across the entire cohort, for both baseline and follow-up. We assumed that the proportion of time the phone is used to call at low (800–900 MHz) and at high frequencies (1800–2100 MHz) were assumed to be 0.36 and 0.64 respectively, in accordance with previous studies (van Wel, 2021; Liorni, 2020) and the RF-EMF default. We assumed that approximately one third of the calls happened on 2G, 3G and 4G (VoLTE; voice over LTE) and assumed that 4G calls result in the same average SAR as 3G (Joshi, 2017). Each device used in the different use scenarios (see next paragraph) was allocated a typical output power as described in Online Supplement Table 2, and as done in previous studies (van Wel, 2021; Liorni, 2020).

2.6. Far-field RF from environmental sources

Exposure from far field sources including mobile phone base stations and broadcast transmitters was estimated from personal measurements collected in a subset of 148 children from the SCAMP cohort between December 2015 and November 2018 (Schmutz, 2022). Following a protocol from several earlier studies (Eeftens, 2018; Roser, 2017), children were asked to carry an ExpoM-RF personal radiofrequency exposimeter (Fields At Work, Zurich, Switzerland (Fields at Work, 2021) for at least 24 h, while behaving as usual and using their phone and any other devices as usual. Meanwhile, they kept track of the duration of time they spent in five main activities: at home, at school, travelling, outside and miscellaneous, using a diary app on a study-provided smartphone which was locked in flight mode. The activity diary was verified by GPS coordinates and corrected where necessary by the study team (Schmutz, 2022). The ExpoM-RF measures 16 frequency bands commonly used by wireless communication and broadcasting services in the range of 87.5 to 5875 MHz and logs a measurement every 4 s.

We summarized the children’s exposures at home, at school and overall, by taking the geometric mean of the children’s personal time-weighted geometric means ($n = 148$) for each of the 16 frequency bands measured by the ExpoM-RF. We considered the resulting far-field exposure was representative of the average reported activity duration for this subset of SCAMP children: 14.1 h at home, 5.7 h at school, 0.8 h outside, 1.1 h in transport and 2.3 h in miscellaneous other environments. Since the ExpoM-RF device is unable to discriminate between different sources of RF-EMF (e.g. if the carrier was using their own mobile phone, or sitting on the bus next to another user), it also measured uplink from the participants' phones. The "own use" contribution was estimated to account for 93% of total uplink in personal measurements (Struchen, 2016). Hence, the personal measurement uplink band contribution was reduced to 7% to eliminate the double count of own phone use in the model, and reflect the environmental contribution only.

2.7. Sociodemographic factors

Sociodemographic factors were collected from different questionnaire assessments: sex was reported by the children themselves in A1, and socio-economic status (SES) and parental education were collected from the parental assessment A5.

2.8. Statistical analysis

All analyses were performed using R version 4.0.3 (R Core Team and R, 2020). We analysed:

1. The extent to which each of the scenarios contributed to the daily total RF-EMF dose to each of these eight tissues, and calculated mean, median and 5th and 95th percentiles of the total dose to each of these eight organs.
2. The increase in estimated daily dose in mJ/kg/day at follow-up (as compared to baseline) for the subset of children whose dose we were able to model at both time points. We evaluated this as a mixed model (R package "lme4") with random intercepts for personal ID.
3. For the same subset of children whose dose we modelled at both time points, we calculated the correlation R^2 of estimated dose between baseline and follow-up.
4. The contribution of each of the 12 exposure scenarios to the total dose, both in absolute [mJ/kg/day] and relative (% of the total) terms.
5. Differences in estimated dose by sex, ethnicity, SES, phone ownership (smartphone, barphone or no phone) and age. Separately baseline and follow-up, we used a multivariable generalized linear regression model, evaluating the association between log(dose) and mutual associations of each of the variables mentioned above. In addition, for those participants for whom a dose estimate was available at both time points, we modelled if the change between baseline and follow-up (calculated as follow-up minus baseline, for the respective tissues) is related to these same factors. This Δ dose can be negative (i.e. indicating a dose decrease between baseline and follow-up), and therefore change is modelled as an absolute dose increment of 1000 mJ/kg/day (logging negative values is not possible).

3. Results

We were able to perform dose-modelling calculations for 6152 out of 6605 participants for baseline (93.1%) and for 5045 out of 5194 participants for follow-up (97.1%) (Online Supplement, Fig. 1). As detailed in a previous publication (Shen, 2022), loss of follow-up was mainly due to schools dropping out for follow-up assessment and logistical issues with school timetables, and therefore, loss to follow-up was assumed to be at random. Dose estimates were available at both time points for 3384 children. Inability to run the dose model was due to missing input data: participants not reporting the duration of phone calls (baseline n = 65; follow-up n = 43), DECT calls (n = 68; n = 48), phone data use (n = 64; n = 43), tablet use (n = 265; n = 108), laptop use (n = 264; n = 106) and WiFi use (n = 58; n = 0) for baseline and follow-up respectively. Many participants had missing usage data for several of the above.

3.1. Study population characteristics

Children included in baseline dose modelling had a median age of 12.1 years, while those included in the follow-up two years later were a median of 14.2 years old (Table 2). The distributions of sex, socio-economic status and ethnicity were very similar for children included in baseline and follow-up questionnaires and in the group for which we could model dose at both time points (Table 2). Smartphone ownership increased from 73.7% at baseline to 90.1% at follow-up and duration of phone calls, WiFi internet use and mobile network internet use increased accordingly. Duration of calls using DECT phones remained the same. Duration of tablet use decreased, while duration of laptop use increased between baseline and follow-up.

3.2. Modelled daily RF dose to brain tissue

Mean and median (P5-P95) model-estimated daily dose is shown in Fig. 1 for both baseline and follow-up. Of the eight tissues analysed, mean total dose was estimated to be highest to the right temporal lobe for both baseline (1150 mJ/kg/day) and follow-up (1520 mJ/kg/day), followed by the left temporal lobe. Estimated daily dose was lower at baseline than at follow-up for all tissues except the heart ($p < 0.001$). Differences were small for heart and whole body dose, which were estimated at an average of 37.0 mJ/kg/day and 170 mJ/kg/day at baseline and 31.1 mJ/kg/day and 178 mJ/kg/day at follow-up. Mean estimated whole brain dose was on average 347 mJ/kg/day at baseline and 442 mJ/kg/day at follow-up.

3.3. Longitudinal development of RF-EMF dose over time

We note that the populations at baseline (n = 6152) and follow-up (n = 5045), displayed in Fig. 1, were partly different, and a direct comparison is best made based on the 3384 adolescents for whom dose modelling was successful at both baseline and follow-up to avoid possible selection bias. Table 3 shows the estimated increase of daily modelled dose to each tissue at follow-up (compared to baseline), for this select group.

Fig. 2 shows the correlation between daily dose calculated at baseline and at follow-up for the 3384 children whose dose could be estimated at both time points. A low, but significant positive correlation was observed between dose estimated at these different time points for all tissues, with highest Pearson correlation for whole-body dose (R = 0.36) and lowest for heart (R = 0.25).

3.4. Contributions of RF-EMF scenarios to the total dose

Fig. 3 shows the mean absolute and relative contributions of the twelve scenarios to the total dose for each of the eight tissues, and in addition, the median (and 5th and 95th percentiles) are presented in Online Supplement Tables 3A to 3D. Mobile phone calls on the 2G network are the predominant contributor to the total dose for all six head and brain-related tissues, contributing on average 55.1% to 66.0% for baseline and 61.7% to 74.0% for follow-up. Contributions to whole body dose were quite diverse, and –for baseline and follow-up respectively– were predominantly made up of mobile network calls on the 2G network (16.8% and 17.3%), contributions from WiFi devices (e.g. router, game console and smart TV; 22.6% and 23.8%), mobile phone data use (18.0% and 25.8%) and tablet use (16.6% and 9.2%). Dose to the heart was in general much lower, and predominantly originated from mobile phone data (45.1% and 62.8%) and tablet use (44.5% and 24.6%) for baseline and follow-up, but here we note that these relatively low results are because the model does not specify a SAR transfer function for devices which were used near the head (e.g. mobile phones)

Table 2
Study population characteristics and duration of mobile communication technologies at baseline and follow-up.

	Baseline			Follow-up			Comparison
	Questionnaire N = 6605	Dose modelling N = 6152	Dose modelling both [a] N = 3384	Questionnaire N = 5194	Dose modelling N = 5045	Dose modelling both [a] N = 3384	*p*-value [b]
Age	N = 6605	N = 6152	N = 3384	N = 5194	N = 5045	N = 3384	N/A
median (IQR)	12.1 (11.8, 12.3)	12.1 (11.8, 12.4)	12.0 (11.8, 12.3)	14.2 (13.9, 14.6)	14.2 (13.9, 14.6)	14.2 (13.9, 14.6)	
Sex	N = 6605	N = 6152	N = 3384	N = 5194	N = 5045	N = 3384	N/A
Female	3467 (52.5%)	3203 (52.1%)	1944 (57.4%)	2818 (54.3%)	2766 (54.8%)	1944 (57.4%)	
Male	3138 (47.5%)	2949 (47.9%)	1440 (42.6%)	2376 (45.7%)	2279 (45.2%)	1440 (42.6%)	
SES [c]	N = 5947	N = 5568	N = 3272	N = 4616	N = 4516	N = 3272	N/A
High	3417 (57.5%)	3192 (57.3%)	1929 (59%)	2711 (58.7%)	2647 (58.6%)	1929 (59%)	
Other	2530 (42.5%)	2376 (42.7%)	1343 (41%)	1905 (41.3%)	1869 (41.4%)	1343 (41%)	
Ethnicity	N = 6499	N = 6094	N = 3383	N = 5116	N = 5003	N = 3383	N/A
White	2795 (43%)	2580 (42.3%)	1461 (43.2%)	2287 (44.7%)	2236 (44.7%)	1461 (43.2%)	
Asian	1735 (26.7%)	1631 (26.8%)	900 (26.6%)	1356 (26.5%)	1334 (26.7%)	900 (26.6%)	
Black	1000 (15.4%)	945 (15.5%)	499 (14.8%)	728 (14.2%)	705 (14.1%)	499 (14.8%)	
Mixed race	723 (11.1%)	701 (11.5%)	386 (11.4%)	554 (10.8%)	542 (10.8%)	386 (11.4%)	
Other/not interpretable	246 (3.8%)	237 (3.9%)	137 (4%)	191 (3.7%)	186 (3.7%)	137 (4%)	
Phone ownership	N = 6547	N = 6152	N = 3384	N = 5158	N = 5045	N = 3384	$p < 0.001$ [d]
Smartphone	4828 (73.7%)	4530 (73.6%)	2455 (72.5%)	4647 (90.1%)	4544 (90.1%)	3084 (91.1%)	
Bar phone	653 (10%)	609 (9.9%)	354 (10.5%)	97 (1.9%)	96 (1.9%)	44 (1.3%)	
No phone	1066 (16.3%)	1013 (16.5%)	575 (17%)	414 (8%)	405 (8%)	256 (7.6%)	
Duration of phone calls	N = 6540	N = 6152	N = 3384	N = 5151	N = 5045	N = 3384	$p < 0.001$ [e]
Median (IQR) [min/day]	6 (3, 14.9)	6 (3, 14.1)	5.1 (3, 14.1)	8.7 (3, 29.3)	8.4 (3, 29.3)	8.4 (3, 26)	
Duration of DECT calls	N = 6537	N = 6152	N = 3384	N = 5146	N = 5045	N = 3384	$p = 0.141$ [e]
Median (IQR) [min/day]	0.9 (0, 3)	0.9 (0, 3)	0.9 (0, 3)	0.9 (0, 3)	0.9 (0, 3)	0.9 (0, 3)	
Duration of WiFi internet use	N = 6541	N = 6152	N = 3384	N = 5151	N = 5045	N = 3384	$p < 0.001$ [e]
Median (IQR) [min/day]	18.4 (0.4, 90.2)	18.6 (0.4, 94.5)	14.8 (0, 67.6)	94.5 (31.1, 210)	94.5 (31.1, 210)	94.5 (31.1, 189.5)	
Duration of mobile network internet use	N = 6541	N = 6152	N = 3384	N = 5151	N = 5045	N = 3384	$p < 0.001$ [e]
Median (IQR) [min/day]	6.2 (0.2, 24.5)	6.2 (0.2, 24.5)	4.9 (0, 22.3)	16.9 (6.2, 35.6)	16.9 (6.2, 35.6)	15.6 (6.2, 33.1)	
Duration of tablet use	N = 6340	N = 6152	N = 3384	N = 5086	N = 5045	N = 3384	$p < 0.001$ [e]
Median (IQR) [min/day]	23.8 (1.6, 65.4)	23.8 (1.6, 65.4)	23.5 (1.1, 62.1)	6.8 (0, 51.4)	7 (0, 53)	6.6 (0, 49.2)	
Duration of laptop use	N = 6341	N = 6152	N = 3384	N = 5088	N = 5045	N = 3384	$p < 0.001$ [e]
Median (IQR) [min/day]	20.5 (1.1, 74.6)	20.5 (1.3, 74.6)	20.5 (1.1, 68.6)	27.5 (3.3, 105)	27.5 (3.3, 105)	27.5 (3.3, 105)	

[a] Children for whom both baseline and follow-up dose modelling were successful (N = 3384).
[b] We compare time-varying factors, for the changes within the group of children for whom both baseline and follow-up dose modelling were successful (n = 3384).
[c] The categories moderate SES and low SES were combined because the latter category would be very small otherwise.
[d] Fisher's exact test (R package "stats").
[e] ANOVA (R package "tableone").

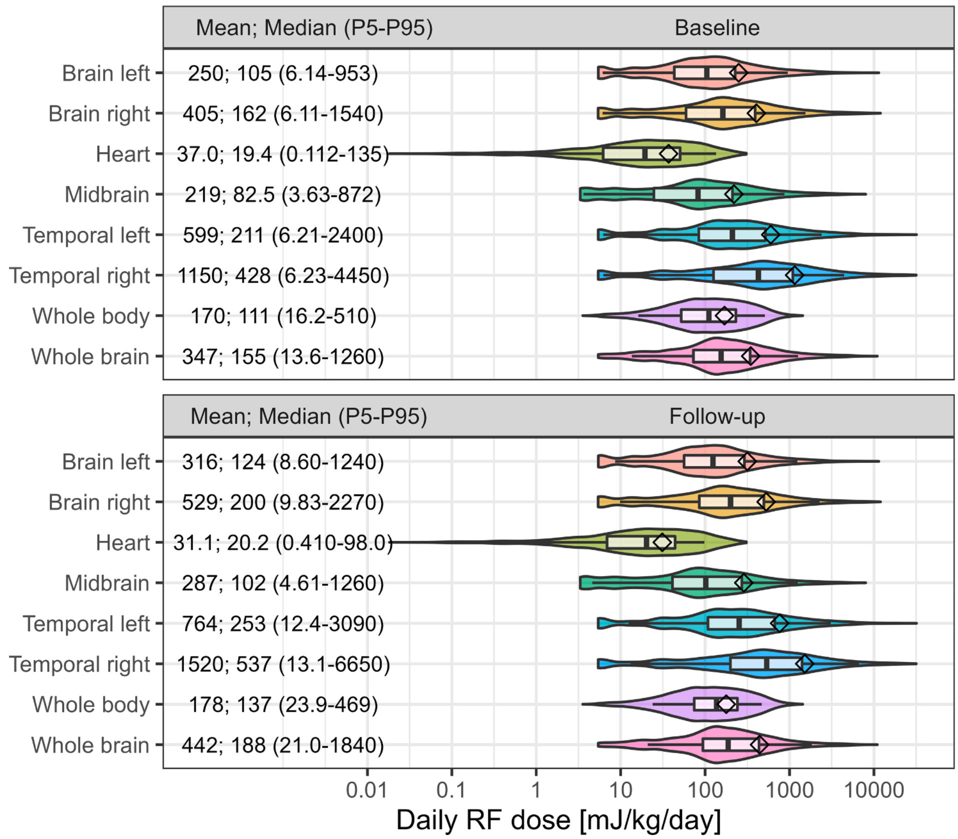

Fig. 1. Mean and median (P5-P95) daily dose of RF-EMF in mJ/kg/day for baseline (n = 6152) and follow-up (n = 5045) for each of eight specific tissues as modelled by the dose model.

Table 3
Increase of daily modelled dose at follow-up (as compared to baseline) for each tissue (n = 3384).

Tissue	Increase at follow-up [mJ/kg/day] (95% confidence interval) [a]
Brain left	77.14 (53.18, 101.09)
Brain right	129.98 (94.85, 165.12)
Heart	−3.57 (-5.16, −1.99)
Midbrain	72.25 (52.75, 91.74)
Temporal left	192.3 (127.98, 256.62)
Temporal right	379.95 (274.72, 485.18)
Whole body	18.05 (12.54, 23.57)
Whole brain	104.47 (77.21, 131.74)

[a] Results of a mixed model with random intercept for each participant.

or for far field.

Differences between the baseline and follow-up were generally small, but at follow-up, a slightly higher percentage of the total dose to all tissues originated from mobile phone related scenarios: notably mobile network calls on the 2G network and mobile phone data use. Meanwhile, there was a decrease in both absolute and relative dose contributions originating from DECT phones and tablets between baseline and follow-up.

3.5. Associations between socio-demographic factors and modelled daily RF dose

Table 4 shows the associations between whole body and whole brain dose and sex, ethnicity, socio-economic status, smartphone ownership and age, for both baseline and follow-up. Associations for the six other tissues (brain left, brain right, heart, midbrain, temporal left and temporal right) can be found in Online Supplement 4.

On average, boys had a slightly higher whole body dose than girls for baseline, but this reversed in the follow-up. Boys experienced a lower dose to the brain than girls did, and this difference became larger between baseline and follow-up, due to a smaller increase in dose in boys. In terms of ethnicity, black children had the highest whole body and whole brain dose at baseline and follow-up, while Asian children had the lowest. The associations with SES tended towards a slightly higher dose for “Other” (including both the moderate SES and low SES categories) as opposed to “High” NSSEC-5 children for whole body and whole brain dose, both at baseline and follow-up, where NSSEC-5 is the National Statistics Socioeconomic Classification using 5 levels (Rose and Pevalin, 2010). Bar phone ownership resulted in a substantially lower dose for both whole body and whole brain than smartphone ownership (the reference), because of lower use, and this difference was even more pronounced for whole body than for whole brain. Having no phone at all was associated with an even lower whole body dose of on average around 40% and 42% (baseline and follow-up, respectively) that of smartphone owners, and a whole brain dose which was only 14% and 14% of that of smartphone owners. Large increases in estimated both whole brain and whole body dose occurred in children who did not have a smartphone at baseline, but acquired one at follow-up (n = 733). Children who had a smartphone at baseline rarely gave it up at follow-up (n = 104), but unsurprisingly, this was associated with a large reduction in estimated dose, most notably for whole brain. Even though the age range within the baseline and follow-up assessments was limited, because all children were recruited from the same school year, body and whole brain dose were still found to increase significantly with age at baseline. This age-gradient was no longer present at follow-up.

4. Discussion

This study describes the results of a comprehensive RF-EMF dose model for the participants of the SCAMP cohort at both baseline and

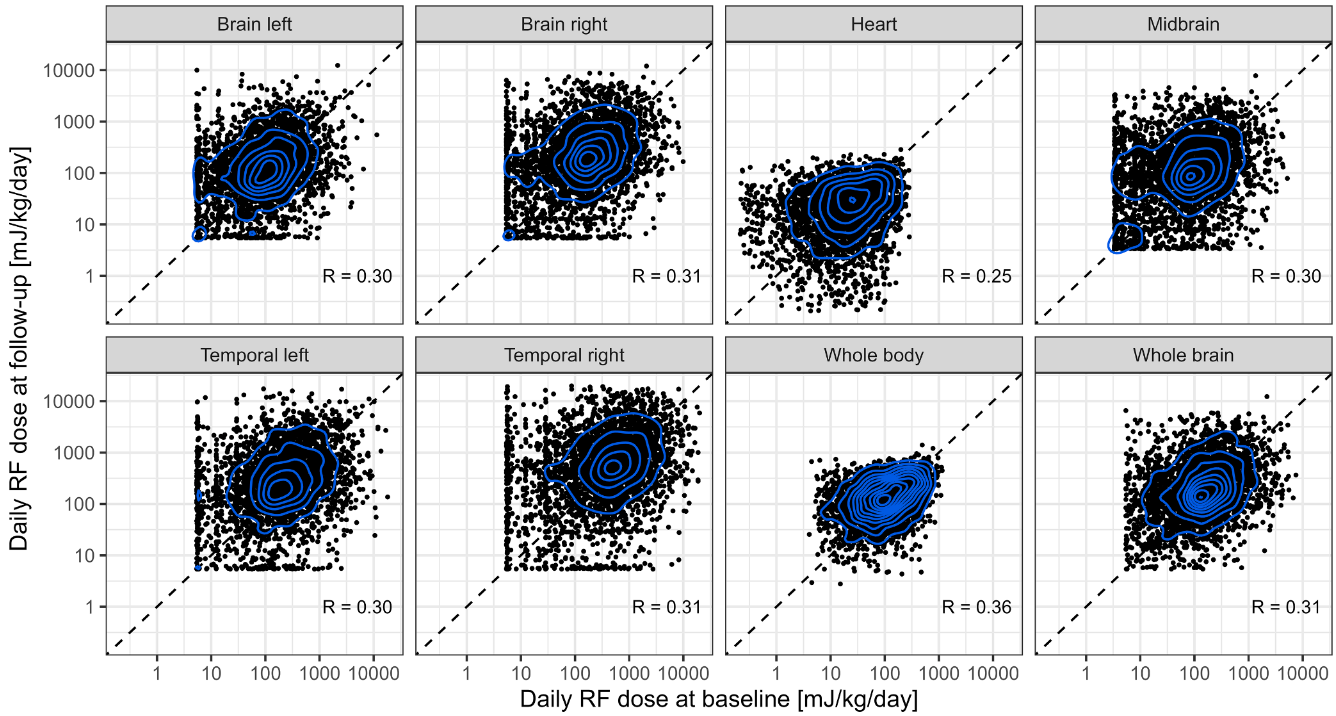

Fig. 2. Correlation between estimated RF-EMF dose at baseline and follow-up by tissue, for the subgroup of 3384 children whose doses could be estimated at both time points. The blue lines mark contour lines of a 2D density estimation of the point cloud. The dashed line marks the y = x line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

follow-up, which will be used in further epidemiological analyses for the SCAMP study. We found that phone calls on the 2G network contribute most of the total daily dose at both the baseline and follow-up time points in exposure to the head and brain-related tissues.

4.1. Comparison to other studies

Median whole body (111 mJ/kg/day at baseline; 137 mJ/kg/day at follow-up) and whole brain dose (155 mJ/kg/day; 188 mJ/kg/day at follow-up) in our sample were in the same range as previously observed in Spanish and Dutch children aged 9–12 years (whole body: 84 mJ/kg/day; whole brain: 82 mJ/kg/day) (Birks, 2021) using the same integrated exposure model. They were also similar to the doses observed for Spanish and Swiss adolescents aged 14 to 18 years (whole body: 42 mJ/kg/day and whole brain: 330 mJ/kg/day) (Birks, 2021) and adults from four European countries (whole body: 184 mJ/kg/day, whole brain: 204 mJ/kg/day). Differences mostly reflect different patterns of mobile phone call duration.

Over the course of our study, dose contributions from environmental sources and use of devices, which are typical for communal use, such as DECT phones and WiFi routers, and tablets did not change much. In contrast, an increase with age in mobile phone use for data transmission and calling resulted in higher corresponding contributions to the dose estimates at follow-up compared to baseline: a pattern which was also observed in previous studies (Birks, 2021). Similar to our study, previous research has also found that females and older children report longer call duration (Langer, 2017; Birks, 2021), more data usage (Birks, 2021) and generally higher doses of RF-EMF to the head and brain (Birks, 2021). Smartphone ownership (versus owning a bar phone or no phone at all) was the predominant determinant of estimated dose both at baseline and follow-up. Unsurprisingly, the acquisition or giving up of a smartphone was a strong determinant of the change in estimated dose between baseline and follow-up.

The low correlation between estimated dose at baseline and at follow-up suggests that dose estimates have a limited longevity, and may not be representative for a child's typical (long-term) exposure situation. This may indicate that over a period of two years, usage and behaviour with regard to use of mobile communication technologies changes a lot in this age group, which is indeed known as a transition from childhood to adolescence.

4.2. Strengths and limitations

This is the first study to present repeated estimates of modelled RF dose in a large number of children prospectively, allowing for a longitudinal change analysis. Compared to a previous cohort study (Roser, 2015) the SAR transfer algorithms have been updated in response to technological development and dosimetric research and have been expanded to 64 specific tissues and organs within the body (Liorni, 2020). We presented results for eight tissues most relevant for the SCAMP study. However, we note that no SAR transfer function was available for dose to the heart for devices which were used near the head (e.g. mobile phones) or for far field. This explains the relatively low (and likely underestimated) total absolute dose to the heart as compared to other organs, estimated, as well as a different distribution.

A particular asset of the RF-EMF dose model is the combination of near-field (usage and behaviour-related) and far-field (environmental, e.g. mobile phone base stations, WiFi access points, broadcast towers) sources, allowing us to consider exposure resulting from a total of 12 common exposure scenarios. This allows for a targeted assessment of dose to organs of interest to serve the analysis of the health outcomes of interest in subsequent epidemiological analyses.

The RF-EMF dose model considers source specific attributes (source type, output power, operating frequency), personal characteristics (body mass, weight), and the specific exposure scenario (position relative to the body, type of use, duration of use). These elements allow for more precise dose estimation and insight into the contribution of different usage scenarios to the total RF-EMF dose received, compared to studies which merely assess RF-EMF dose from mobile phone calls (e.g. by questionnaire) or geographic proximity to stationary environmental

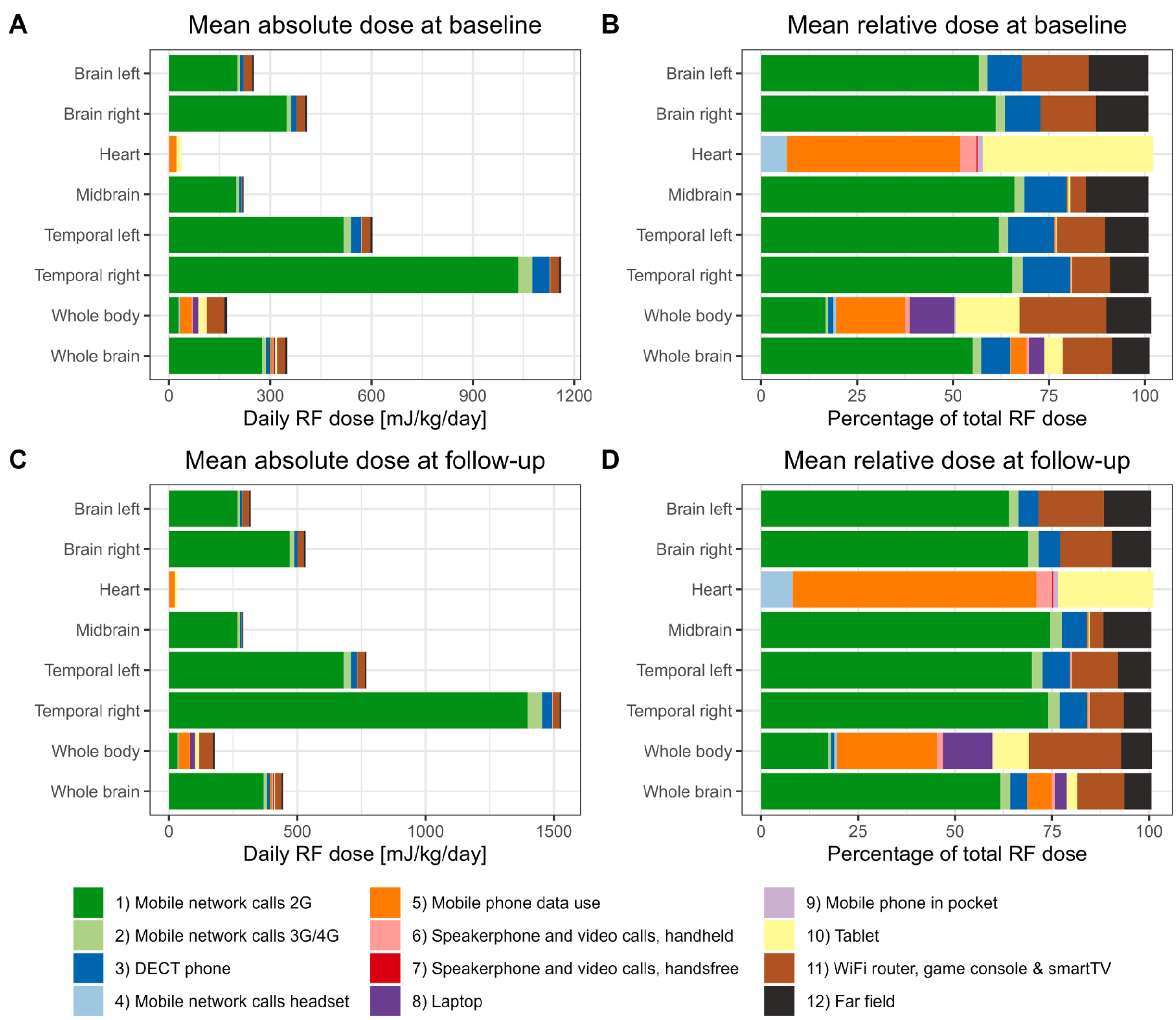

Fig. 3. Estimated dose to RF-EMF at baseline (n = 6152) (A, B) and follow-up (n = 5045) (C, D), shown as average absolute dose [mJ/kg/day] for all participants (A, C) and as the average percentage of the total for all participants (B, D).

sources (e.g. by spatial modelling base station exposure). Eventually, this approach will be a good basis for differentiation between potential health effects related to (biophysical) exposure to RF-EMF (e.g. tinnitus, migraine, headache, sleep quality and fatigue (Röösli, 2021), in contrast to indirect effects related to e-media usage such as sleep deprivation, addiction, reduced physical activity, blue light etc. To date, mobile phone calls contribute substantially to all dose measures whereas other types of e-media use are less relevant, in particular for the RF-EMF dose to the head. However, with switching off 2G and a trend of network densification and corresponding lower output power of mobile phones, the RF-EMF dose contribution from own devices may decrease in the future, and contributions from far field sources may become more relevant (Mazloum, 2019). In our study, we used the averaged personal measurements from a subset of participants, but could not obtain data from the whole cohort, which is a limitation. This assumption would have resulted in some Berkson error, but since the far field contribution is on average a minor contribution to the total, we do not expect this to lead to a major decrease in study power. Given the future network trends, it will thus be crucial to put more effort into the individual estimates of far field RF-EMF sources, which eventually enables the disentanglement of RF-EMF exposure and usage for epidemiological research.

In this application within the SCAMP study, we considered a large sample size and gathered detailed information on many aspects of mobile technology use at an individual level. Repeated RF-EMF dose modelling will enable a longitudinal epidemiological analysis of potential associations with health-related endpoints, which have also been collected at multiple time points.

It needs to be emphasized that the RF-EMF dose model relies heavily on detailed input data, which (apart from the far-field dose contribution) is based on self-reporting of technology usage and related behaviour, also in previous applications (van Wel, 2021; Cabré-Riera, 2020; Birks, 2021). Such self-reported information is subject to uncertainty. Self-reported mobile phone use was validated for a subset of 350 SCAMP children at baseline using operator data (Mireku, 2018). Self-reported usage was able to distinguish between high and low use (Mireku, 2018), also in other studies (Langer, 2017). Nevertheless, children overestimated their call duration in 45.1% and 59.2% of cases on weekdays and weekend respectively, while only 16.0% and 11.4% underestimated their call duration (Mireku, 2018). We acknowledge that the estimated dose due to phone calls may therefore have been overestimated in this cohort. Conversely, self-reported mobile data use cannot easily be validated with operator data, because participants tend to report time spent surfing, whereas operators record quantity of data transferred. Therefore, there is little consensus and a lack of validation for the validity of the duration of self-reported data use (Goedhart, 2015). Moreover, the output power of devices depends strongly on the type of data use and the network quality (Joshi, 2017; Mazloum, 2019;

Table 4
Determinants of whole body and whole brain dose, for baseline, follow-up, and change between baseline and follow-up.

			Baseline (n = 6152)		Follow-up (n = 5045)		Change (n = 3384)	
Tissue [a]	Determinant		Ratio (95% CI) [b]	P-value	Ratio (95% CI) [b]	P-value	Ratio (95% CI) [b]	P-value
Whole body	Sex [c]	Male	1.07 (1.02–1.13)	0.01	0.94 (0.90–0.99)	0.02	0.98 (0.96–0.99)	<0.001
	Ethnicity [d]	Black	1.38 (1.27–1.49)	<0.001	1.26 (1.17–1.36)	<0.001	0.98 (0.96–0.99)	0.01
		Asian	0.95 (0.89–1.01)	0.11	1.00 (0.94–1.07)	0.94	1.00 (0.99–1.02)	0.67
		Mixed	1.18 (1.08–1.28)	<0.001	1.12 (1.03–1.22)	0.01	0.99 (0.98–1.01)	0.58
		Other/N.I.	1.05 (0.92–1.21)	0.48	1.05 (0.91–1.21)	0.47	1.00 (0.97–1.03)	0.86
	SES [e]	Other	1.13 (1.07–1.19)	<0.001	1.11 (1.05–1.17)	<0.001	1.01 (1.00–1.02)	0.17
	Smartphone ownership [f]	Barphone	0.58 (0.53–0.64)	<0.001	0.61 (0.51–0.74)	<0.001		
		No phone	0.40 (0.37–0.43)	<0.001	0.42 (0.38–0.46)	<0.001		
		Got a smartphone					1.06 (1.05–1.08)	<0.001
		Gave up smartphone					0.95 (0.91–0.98)	<0.001
	Age [g]	Age	1.15 (1.08–1.23)	<0.001	0.97 (0.92–1.02)	0.26	1.02 (1.00–1.03)	0.01
Whole brain	Sex [c]	Male	0.90 (0.85–0.95)	<0.001	0.86 (0.80–0.92)	<0.001	0.98 (0.93–1.04)	0.53
	Ethnicity [d]	Black	1.38 (1.27–1.51)	<0.001	1.38 (1.24–1.53)	<0.001	1.09 (1.00–1.19)	0.05
		Asian	0.91 (0.84–0.97)	0.01	0.91 (0.84–0.99)	0.04	0.98 (0.92–1.05)	0.63
		Mixed	1.18 (1.07–1.30)	<0.001	0.99 (0.89–1.11)	0.88	0.95 (0.87–1.04)	0.26
		Other/N.I.	1.07 (0.92–1.25)	0.37	1.12 (0.93–1.35)	0.23	1.06 (0.91–1.23)	0.44
	SES [e]	Other	1.11 (1.04–1.17)	<0.001	1.14 (1.06–1.22)	<0.001	1.00 (0.95–1.06)	0.91
	Smartphone ownership [f]	Barphone	0.75 (0.68–0.83)	<0.001	0.88 (0.68–1.14)	0.33		
		No phone	0.14 (0.13–0.16)	<0.001	0.14 (0.12–0.15)	<0.001		
		Got a smartphone					1.24 (1.16–1.33)	<0.001
		Gave up smartphone					0.72 (0.61–0.85)	<0.001
	Age [g]	Age	1.14 (1.06–1.23)	<0.001	1.05 (0.98–1.12)	0.17	1.12 (1.04–1.21)	<0.001

[a] For tissues whole body and whole brain only, for other tissues see online supplement 4.
[b] Based on a generalized linear model evaluating log(dose) as a function of the determinants (for baseline and follow-up) and change between baseline and follow-up (calculated as follow-up minus baseline, for the respective tissues) as Δ dose for an increment of 1000 mJ/kg/day.
[c] Female was the reference.
[d] White was the reference.
[e] High SES was the reference, "other" includes both moderate and low SES.
[f] Having a smartphone was the reference for baseline and follow-up, whereas "no change" was the reference and most common situation (n = 2247) for the change analyses, as opposed to getting a smartphone (n = 733), or giving it up (n = 104) between baseline and follow-up.
[g] Ratio defined for a 1-year increment in age, where age is regarded as Δ age between baseline and follow-up, for the change analyses.

Persson, 2012). Thus, duration of use alone may not be the most appropriate metric for RF-EMF dose modelling (Calderón, 2022). Similarly, we are not aware of any studies that validate self-reported tablet or laptop use, but doubt that this would be feasible to monitor objectively at a large scale, and therefore think that self-reported use is the best possible approximation of use that is feasible to obtain for large study populations. Given all these uncertainties, there is a possibility that the low correlation between RF-EMF dose estimates at baseline and follow-up may not only reflect dynamic changes in individual usage behaviour but also inaccuracies when estimating the own usage of various RF-EMF sources.

Since the RF-EMF dose model has been developed after the SCAMP study questionnaire, some model inputs were not considered in the questionnaire and we used default values instead. For example: the model offers the possibility to define the duration of smart watch and body area network use, whether people hold their smartphone in front of their face or on top of their belly while surfing the internet. Even if such detailed information had been included in the questionnaire, information might be highly uncertain. Unfortunately, the dose model does not include specific scenarios for gaming, using a video console or watching smart TV while these activities are common in the young age group. We had assessed these activities as WiFi exposure, since to the best of our knowledge, no data have been published on the RF-EMF exposure during such activities.

A more critical issue for dose estimation is the type of mobile phone network. The RF-EMF dose model puts the output power of calling on a mobile phone on the 2G and 3G networks at 89.7 mW and 0.45 mW respectively, which is a large difference and explains the relative importance of the 2G calls for total dose. The model does not include a scenario for 4G, but we assumed the emitted radiation to be equal to that of 3G (Joshi, 2017). We did not have information on proportion of 2G/3G/4G use in the cohort (5G was still not relevant at the time of data collection), and assumed that 2G, 3G and 4G were each used approximately one third of the time for both baseline and follow-up, but this assumption could not be validated. Considering the importance of 2G in dose modelling, any change of this ratio within the two years would have noticeable impact on the dose estimate. Thus, we cannot rule out that decrease in 2G use over the study period may have overcompensated the increased usage, which would mean that the RF-EMF dose would have actually decreased over time. However, such data or literature are not publicly accessible. Lack of such technical data and rapid technological development is an important challenge for RF-EMF exposure assessment. With 5G being introduced and dynamic changes of output power of communication devices in response to network changes, the RF-EMF dose will soon need an upgrade to enable the more specific exposures resulting from Voice over LTE and 5G technology (Joshi, 2020).

5. Conclusion

This study in a large sample of adolescents confirms that mobile phone use is the main contributor to daily RF-EMF dose for the whole body and various brain regions. The correlation between individual dose estimates within two years was relatively low, likely reflecting both dynamic changes in mobile device usage in this age group, as well as uncertainty when estimating own wireless communication use. This calls for repeated exposure assessment in longitudinal studies on RF-EMF.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2023.107737.

References

Birks, L.E., et al., 2018. Spatial and temporal variability of personal environmental exposure to radio frequency electromagnetic fields in children in Europe. Environ. Int. 117, 204–214.

Birks, L.E., et al., 2021. Radiofrequency electromagnetic fields from mobile communication: Description of modeled dose in brain regions and the body in European children and adolescents. Environ. Res. 193, 110505.

Bruton, J., et al., 2020. Enabling participation of Black and Minority Ethnic (BME) and seldom-heard communities in health research: A case study from the SCAMP adolescent cohort study. Research for All.

Cabré-Riera, A., et al., 2020. Estimated whole-brain and lobe-specific radiofrequency electromagnetic fields doses and brain volumes in preadolescents. Environ. Int. 142, 105808.

Cabré-Riera, A., et al., 2021. Association between estimated whole-brain radiofrequency electromagnetic fields dose and cognitive function in preadolescents and adolescents. Int. J. Hyg. Environ. Health 231, 113659.

Calderón, C., et al., 2022. Estimation of RF and ELF dose by anatomical location in the brain from wireless phones in the MOBI-Kids study. Environ. Int. 163, 107189.

Chetty-Mhlanga, S., et al., 2020. Different aspects of electronic media use, symptoms and neurocognitive outcomes of children and adolescents in the rural Western Cape region of South Africa. Environ. Res. 184, 109315.

Christ, A., et al., 2010. Age-dependent tissue-specific exposure of cell phone users. Phys. Med. Biol. 55 (7), 1767.

Eeftens, M., et al., 2018. Personal exposure to radio-frequency electromagnetic fields in Europe: Is there a generation gap? Environ. Int. 121, 216–226.

Feychting, M., 2005. Non-cancer EMF effects related to children. Bioelectromagnetics 26 (S7), S69–S74.

Fields at Work, Company website. http://www.fieldsatwork.ch/ [Accessed: 9 February 2021], 2021.

Foerster, M., et al., 2018. A prospective cohort study of adolescents' memory performance and individual brain dose of microwave radiation from wireless communication. Environ. Health Perspect. 126 (7), 077007.

Foerster, M., et al., 2019. Impact of adolescents' screen time and nocturnal mobile phone-related awakenings on sleep and general health symptoms: a prospective cohort study. Int. J. Environ. Res. Public Health 16 (3), 518.

Goedhart, G., et al., 2015. Using software-modified smartphones to validate self-reported mobile phone use in young people: a pilot study. Bioelectromagnetics 36 (7), 538–543.

Ishihara, T., et al., 2020. Exposure to Radiofrequency Electromagnetic Field in the High-Frequency Band and Cognitive Function in Children and Adolescents: A Literature Review. Int. J. Environ. Res. Public Health 17 (24), 9179.

Jalilian, H., et al., 2019. Public exposure to radiofrequency electromagnetic fields in everyday microenvironments: An updated systematic review for Europe. Environ. Res. 176, 108517.

Joshi, P., et al., 2017. Output power levels of 4G user equipment and implications on realistic RF EMF exposure assessments. IEEE Access 5, 4545–4550.

Joshi, P., et al., 2020. Actual output power levels of user equipment in 5G commercial networks and implications on realistic RF EMF exposure assessment. IEEE Access 8, 204068–204075.

Kheifets, L., et al., 2005. The sensitivity of children to electromagnetic fields. Pediatrics 116 (2), e303–e313.

Langer, C.E., et al., 2017. Patterns of cellular phone use among young people in 12 countries: Implications for RF exposure. Environ. Int. 107, 65–74.

Lauer, O., et al., 2013. Combining near-and far-field exposure for an organ-specific and whole-body RF-EMF proxy for epidemiological research: a reference case. Bioelectromagnetics 34 (5), 366–374.

Liorni, I., et al., 2020. Evaluation of Specific Absorption Rate in the Far-Field, Near-to-Far Field and Near-Field Regions for Integrative Radiofrequency Exposure Assessment. Radiat. Prot. Dosim. 190 (4), 459–472.

Mazloum, T., et al., 2019. RF-EMF exposure induced by mobile phones operating in LTE small cells in two different urban cities. Ann. Telecommun. 74 (1), 35–42.

Mireku, M.O., et al., 2018. Total recall in the SCAMP cohort: validation of self-reported mobile phone use in the smartphone era. Environ. Res. 161, 1–8.

Mireku, M.O., et al., 2019. Night-time screen-based media device use and adolescents' sleep and health-related quality of life. Environ. Int. 124, 66–78.

Pereira, F.S., et al., 2020. Impact of problematic smartphone use on mental health of adolescent students: Association with mood, symptoms of depression, and physical activity. Cyberpsychol. Behav. Soc. Netw. 23 (9), 619–626.

Persson, T., et al., 2012. Output power distributions of terminals in a 3G mobile communication network. Bioelectromagnetics 33 (4), 320–325.

R Core Team, *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/. 2020.

Röösli, M., et al., 2021. The effects of radiofrequency electromagnetic fields exposure on tinnitus, migraine and non-specific symptoms in the general and working population: A protocol for a systematic review on human observational studies. Environ. Int. 157, 106852.

Rose, D., Pevalin, D., 2010. Volume 3 the national statistics socio-economic classification:(rebased on the SOC2010) user manual. Palgrave Macmillan, Basingstoke, England.

Roser, K., et al., 2015. Development of an RF-EMF exposure surrogate for epidemiologic research. Int. J. Environ. Res. Public Health 12 (5), 5634–5656.

Roser, K., et al., 2017. Personal radiofrequency electromagnetic field exposure measurements in Swiss adolescents. Environ. Int. 99, 303–314.

Schmutz, C., et al., 2022. Personal radiofrequency electromagnetic field exposure of adolescents in the Greater London area in the SCAMP cohort and the association with restrictions on permitted use of mobile communication technologies at school and at home. Environ. Res. 212, 113252.

Shen, C., et al., 2021. Digital technology use and BMI: evidence from a cross-sectional analysis of an adolescent cohort study. J. Med. Internet Res. 23 (7), e26485.

Shen, C., et al., 2022. Bidirectional associations between sleep problems and behavioural difficulties and health-related quality of life in adolescents: Evidence from the SCAMP longitudinal cohort study. JCPP Adv. 2 (3), e12098.

Struchen, B.R., Katharina; Schwob, Benjamin; Meier, Noemi; Fischer, Jonas; Eeftens, Marloes; Röösli, Martin, *Personal RF-EMF exposure in Switzerland: Differences in exposure between adolescents, parents, young adults and community types.* Annual Meeting of the Bioelectromagnetics Society and the European BioElectromagnetics Association, 5-10 June 2016, Ghent, 2016.

Sudan, M., et al., 2016. Trends in cell phone use among children in the Danish national birth cohort at ages 7 and 11 years. J. Eposure Sci. Environ. Epidemiol. 26 (6), 606–612.

Thomas, S., et al., 2010. Use of mobile phones and changes in cognitive function in adolescents. Occup. Environ. Med. 67 (12), 861–866.

Toledano, M.B., et al., 2019. Cohort profile: the study of cognition, adolescents and mobile phones (SCAMP). Int. J. Epidemiol. 48 (1), 25–26l.

van Wel, L., et al., 2021. Radio-frequency electromagnetic field exposure and contribution of sources in the general population: an organ-specific integrative exposure assessment. J. Eposure Sci. Environ. Epidemiol. 1–9.