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Longitudinal study of exposure to radio frequencies at population scale

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ABSTRACT

Evaluating exposure to radio frequencies (RF) at population-scale is important for conducting sound epidemiological studies about possible health impact of RF radiations. Numerous studies reported population exposure to RF radiations used in wireless telecommunication technologies, but used very small population samples. In this context, the real exposure of the population at scale remains poorly understood. Here, to the best of our knowledge, we report the largest crowd-based measurement of population exposure to RF produced by cellular antennas, Wi-Fi access points, and Bluetooth devices for 254,410 unique users in 13 countries from January 2017 to December 2020. First, we present methods to assess the population exposure to RF radiations using smartphone measurements obtained using the ElectroSmart Android app. Then, we use these methods to evaluate and characterize the evolution of RF exposure. We show that total exposure has been multiplied by 2.3 in the four-year period considered, with Wi-Fi as the largest contributor. The cellular exposure levels are orders of magnitude lower than regulation limits and are not correlated to national regulation policies. The population tends to be more exposed at home; for half of the study subjects, personal Wi-Fi routers and Bluetooth devices contributed to more than 50% of their total exposure. In this work, we showcase how crowdsource-based data allow large-scale and long-term assessment of population exposure to RF radiations.

1. Introduction

The past 20 years witnessed a dramatic increase in the number of radio frequency sources with the global adoption of smartphones as primary connectivity devices, the increased popularity of Bluetooth devices from multimedia to quantified-self usages, and the deployment of new cellular technologies with LTE and now 5G.

The increased exposure to radio frequencies urges us to explore the long-standing and complex scientific question of the long-term impact of radio frequencies on health (IARC, 2011). One way to explore this question is to perform epidemiological studies, that is, to find a correlation between symptoms and exposure to radio frequencies. However, characterizing exposure to radio frequencies is a difficult problem as exposure varies vastly in time and space.

Previous studies have used various methods to measure exposure to radio frequencies. First, spot measurements are taken by monitoring exposure at specific locations for a limited period of time (Gallastegi et al., 2018; Aerts et al., 2018; Fernandez et al., 2020). Such measurements are not representative of exposure of individuals as they fail to capture the spatial and temporal variation. Second, micro-environmental studies compare exposure in different locations such as urban and rural areas, offices and homes locations, or indoor and outdoor environments (Sagar et al., 2018a; Velghe et al., 2019; Urbinello et al., 2014a; Urbinello et al., 2014b; Ramirez-Vazquez et al., 2021; Bhatt et al., 2017). They are usually performed by a specialist and shed light on the difference of exposure at specific locations. However, like spot measurements, they are limited in space and time. Last, personal measurement studies are directly performed by volunteers carrying a measurement instrument (Zeleke et al., 2018; Ramirez-Vazquez et al., 2019, 2021; Bhatt et al., 2018; Birks et al., 2018; Gallastegi et al., 2018; Lahham and Ayyad, 2019). As the instrument is moving with each volunteer, the coverage of each individual is good. However, to characterize a population, the scale is of first importance. The scale is directly conditioned by the type of instrument used (Bhatt et al., 2016). Studies using personal exposimeters are difficult to scale, because exposimeters are costly mobile measurement tools (EME Spy, 2021; ExpoM RF, 2021). Another solution is to leverage on commercial smartphones with either hardware modified (Inyang et al., 2009) or a dedicated measurement app (Goedhart et al., 2015; Kiyohara et al., 2018; Vrijheid et al., 2009; The Cosmos project, 2021; Mazloum et al.,

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2020; Cellraid, 2021; Tawkon, n.d.). Recruiting a large population is a challenge despite the worldwide usage of smartphone. All previous works considered a small number of participants (from a few tens to a few hundreds) for a period of time ranging from a few days to a few months.

Related works show that the exposure varies greatly with time and among individuals (Zeleke et al., 2018; Birks et al., 2018). In addition, environmental and behavioral factors impact exposure, limiting the generalizability of results obtained from small study-groups (Sagar et al., 2018a; Velghe et al., 2019; Eeftens et al., 2018; Sagar et al., 2018b; Bhatt et al., 2017, 2018; Urbinello et al., 2014b; Ramirez-Vazquez et al., 2019, 2021; Birks et al., 2018; Gallastegi et al., 2018; Aerts et al., 2018; Breckenkamp et al., 2012; Lahham and Ayyad, 2019; Zeleke et al., 2018; Urbinello et al., 2014a).

Unlike previous works, we present here the first longitudinal study of exposure at population scale; results span four years (Jan 2017–Dec 2020), from 254,410 unique subjects in 13 countries across Europe, North America, Asia, and Australia. We collected personal measurements using smartphone devices running the ElectroSmart app (ElectroSmart, 2021) that measures the *downlink* Received Signal Strength Indicator (RSSI) of all measurable Wi-Fi access points, Bluetooth devices, and cell towers.

In this paper, we focus on four main questions: i) how exposure evolved from 2017 to 2020; ii) how the surrounding sources impact exposure; iii) how regulations impact exposure; iv) how location impacts exposure. In the rest of this paper, we explain the methods we applied to answer these questions in Section 2 (with additional details in Appendix A). We describe our results in Section 3. We discuss the results and limitations in Section 4 and conclude in Section 5.

2. Methods

In the following, we present the methods we used for collecting and analyzing our dataset.

2.1. Data collection

In this section, we present the ElectroSmart app used to collect the data, the characteristics of the collected dataset, the characterization of the study subjects who performed the measurements, and the ethical and legal considerations.

2.1.1. The ElectroSmart measurement app

ElectroSmart (ElectroSmart, 2021) is an Android consumer app we designed to measure the power that a given smartphone receives from Wi-Fi access points, Bluetooth devices, and cell towers. We designed ElectroSmart to be an easy-to-use tool that offers users transparent information on their exposure to radio frequencies. ElectroSmart can be installed on any Android smartphone running Android 4.1 or later. The app was first launched in August 2016, and as of May 18th, 2021, it had 900,000 downloads and 190,000 active users.

ElectroSmart performs an *exposure scan* every 20 min when used in the background. All scans are periodically collected on our servers. Below, we explain how an exposure scan works and describe the information it collects. We discuss user consent and privacy protection in Section 2.1.4. A scan performs the following actions.

- It creates a timestamp with the local time in Coordinated Universal Time (UTC). This is a slight approximation as signals might not be measured at exactly the same time in a given measurement scan. However, by considering a window of a few seconds, it is easy to attribute all measured signals to a given measurement scan and timestamp (we specifically discuss the case of Bluetooth in Appendix A.2.3).
- It collects characteristics of the smartphone (brand and model) and its Android version.
- It measures the smartphone location in terms of latitude and longitude. Android provides this information by combining GPS, Wi-Fi access points, and cell tower information using a proprietary algorithm.
- It measures the *downlink* Received Signal Strength Indicator (RSSI) of all measurable Wi-Fi access points, Bluetooth devices, and cell towers (we discuss limitations in Section 4.3), along with several source-specific data.
  - For Wi-Fi access points, it collects the Service Set Identifier (SSID), the Basic Service Set Identifier (BSSID), the frequency, and whether the user is connected to this access point.
  - For Bluetooth devices, it collects the device name, the device Media Access Control (MAC) address, and whether the user is bonded to this device.
  - For cell towers, it identifies whether the cell is using a 2G, 3G, 4G, or Code Division Multiple Access Evolution-Data Optimized (CDMA/EVDO) technology. It determines whether the cell is serving (that is, the user is currently connected to this cell), and collects cell identification information, such as the Mobile Network Code (MNC), Mobile Country Code (MCC), or Cell ID (CID), to generates an unique identity for each cell tower.

2.1.2. Dataset characteristics

The cleaned and pre-processed dataset we consider in this paper contains 254,410 user profiles and 3,656 million measured RSSI for the following 13 countries (ordered from the highest to the lowest number of measurements): France, the United States, Italy, Germany, Canada, the United Kingdom, Switzerland, Belgium, Spain, the Netherlands, India, Australia, and Brazil. Although Brazil accounts for only 0.5% of all measurements, it still includes 21.6 million measurements and 2668 unique users.

In this dataset, Wi-Fi represents 58.3% of all measured RSSI, Bluetooth 6.6%, 2G 10.5%, 3G 7.6%, and 4G 17%.

This dataset is the result of multiple cleaning and pre-processing steps on the raw data obtained from the ElectroSmart app, which we discuss in Appendix A.

2.1.3. Characterization of the ElectroSmart users

ElectroSmart is an Android app publicly available on Google Play in the *Tools* category (ElectroSmart, 2021). The acquisition of new users, which are our study subjects, is dominated by organic searches on Google Play on the following keywords: EMF[1] detector, EMF sensor, EMF meter, EMF reader, ElectroSmart. This acquisition represents more than 90% of the total user acquisition, without any significant difference among the considered countries and at any time period. The rest of the acquisition is due to google organic searches on the same terms. We never performed any kind of advertisement or targeted user recruitment.

We acknowledge that the collected population sample is potentially biased toward users with an interest in the measurement of exposure to radio frequencies. Such a bias exists for all studies recruiting volunteers to perform exposure measurements, as it is impossible to recruit users with their consent without interest in the subject.

Nevertheless, our sample is representative of the world-wide population in two aspects: urban/rural ratio and age. We discuss these two aspects in the following.

To evaluate the users geographic location, we used OpenStreetMap's Nominatim (Nominatim, 2021) to map each user GPS coordinate to a rural or urban area for each of the 13 considered countries. Then we compared the identified location with a ground truth found in the open data project of World Bank (Worldbank, 2021). First, we observed a great stability over time of the number of users in urban areas in our dataset: for a given country, the evolution of the percentage of

[1] EMF stands for ElectroMagnetic Field. This is the most common term used by the general audience for radio frequencies.

population in the urban area between 2017 and 2020 is at most 9%. This stability is confirmed by the World Bank open data. Second, when compared with the World Bank open data, we observed a difference in the percentage of users in an urban area higher than 10% for only five countries: Switzerland (11%), Canada (16%), France (17%), Belgium (23%), the USA (25%). We deem this difference is reasonable for our purpose because we still observe for all 13 countries a majority of users in the urban area, which is confirmed by the World Bank dataset.

To evaluate the age distribution of our users we used the Google Firebase Analytics data available for ElectroSmart. Indeed, we embedded the analytics library in ElectroSmart from January 2019. We collected the age distribution of all our users between January 2019 and December 2020 for each country and compared it to the demographic data we obtained from the Web site population pyramid (Population Pyramids, 2019) that is aggregating data from the United Nations. We considered 6 age groups: [18, 24], [25, 34], [35, 44], [45, 54], [55, 64], 65+. Firebase Analytics does not provide any information for ages lower than 18. Then we computed the difference of percentages of the population in each group between our user population and the ground truth provided by population pyramid. We found a difference lower than 10% for most age groups and countries with two notable exceptions. First, for 4 countries the age group [35, 44] is more represented: Italy (12%), Australia (13%), the United Kingdom (14%), the USA (14%). Second, for all countries, the age group 65+ is under-represented from 7% for India to 22% for Italy. In summary, our dataset is reasonably representative of the general population, with an under representation of the age group 65+.

2.1.4. Ethical and legal considerations

We submitted the study protocol to our institutional ethical committee (Inria COERLE (COERLE, 2021). They validated that the present study follows all required ethical and data protection standard as described below.

ElectroSmart requires explicit user consent for all information collection and clearly states that all data could be used for scientific research. In particular, we are fully compliant with the European General Data Protection Regulation (GDPR) (GDPR, 2021).

In addition, ElectroSmart is used anonymously by default, unless a user decides to provide an email address. The email address field is clearly identified as optional.

All scans are associated with a unique user ID. This user ID is randomly generated on our server at the app installation time. It is not linked to any unique smartphone or user information.

2.2. Data analysis

This section contains the methodology we applied to the analysis of the dataset presented in Section 3. The readers who want to focus first on the result can skip this section and directly read Section 3. They can later come back to this section to check the details of our methodology.

2.2.1. Personal exposure definition and calculation

We define personal exposure as the received power from all the electromagnetic field sources on the radio frequency bands exposing humans. The received power is a function of the emitting power as described in Eq. (1) where P_r is the received power, P_e is the emitting power, K is a constant dependant on the emitting and receiving antennas' characteristics, d is the distance to the source, and f is the signal frequency (Friis, 1946). We see in Eq. (1) that distance plays an important role in personal exposure, as does signal frequency: higher frequency signals fade faster than lower ones.

$$P_r = K\left(\frac{1}{4\pi df}\right)^2 P_e \tag{1}$$

The analysis we perform in this paper is based on three main calculation steps that we describe and justify in the following. i) For all computations based on an exposure scan (as defined in Section 2.1.1), we consider the sum of the received power in Watt of all signals in this scan. Computing the sum is relevant because an exposure scan is atomic in terms of time, so it represents all the signals simultaneously exposing an individual. ii) We average the exposure scans of each user per month. This gives a per-user monthly average exposure. The rationale of computing per-user monthly averages is to prevent users with a large number of measurements from biasing the monthly average. iii) For each country, we group the per-user monthly average exposures. When a user has been in different countries for a given month, we compute one monthly average exposure per country. Then, we compute the mean of these per-user monthly average exposures to obtain a monthly average exposure per country. Finally, we obtain the yearly average exposure by computing the mean of the monthly average exposure per country. Computing the yearly average exposure this way avoids bias that could be introduced by months with a larger than average number of users.

2.2.2. Computation of individual exposure reduction when removing connected Wi-Fi sources and bounded Bluetooth devices

For each user and each month, we first compute the per-user monthly average exposure. Then, we collect all connected Wi-Fi sources and bounded Bluetooth devices, and re-compute the per-user monthly average exposure by removing all collected connected sources and bounded devices from the exposure scans. Finally, we compute the difference between the per-user monthly average exposure in each case. Note that in some rare cases, the difference can be negative. This can occur when an exposure scan contains only one connected source. By removing connected sources, we change the number of samples on which we average. As a result, a user with only a few samples could end up with a higher average without connected sources. In this figure, we drop users with a negative gain; they represent 0.92% of all users.

2.2.3. Estimating the electric field Strength from RSSI

We obtain the electric field E in V/m from the measured received power RSSI in dBm with the formula:

$$E = \frac{9.73f\sqrt{50 \times 10^{\frac{P-30}{10}}}}{c\sqrt{G}} \tag{2}$$

where G is the antenna gain, f is the frequency in Hz, P is the power in dBm, and c is the speed of light (Liao, 1977). The antenna gain of the smartphone is unknown, so we assume an isotropic antenna (i.e., $G = 1$). In our dataset, we have access to the cellular frequency f for serving cells only. Therefore, we only keep exposure scans with a serving cell containing a valid frequency (they represent 74.5% of all exposure scans). We sum all the cellular RSSI[2] in each exposure scan and convert the summed RSSI into V/m using the frequency of the serving cell.

2.2.4. Cellular regulation

The maximum allowed exposure of the population is fixed by the ICNIRP international body (ICNIRP, 2020). However, each country is free to lower the maximum exposure depending on local policies. In addition, some countries have policies specific to some areas (e.g., Belgium has different limits for Flanders, Wallonia, and Brussels) or specific to some contexts (e.g., Italy enforces lower exposure near schools). Finally, the limits are specific to the frequencies used by cellular technologies. Here, we specifically focus on the frequencies 900 MHz, 1800 MHz, and 2100 MHz. For each country, we build a regulation limit triplet, one limit per frequency.

[2] As explained in Section 2.2.1, we perform the sum in Watt, and because we only measure the RSSI for the operator declared in the SIM card, we multiply each RSSI by the number of operators in the country in a pre-processing phase (see Appendix A.2.4 for details).

To the best of our knowledge, there is no central repository of exposure limits for all countries. To obtain a regulation limit triplet for each of the 13 countries we consider, we consolidate several sources (WHO, 2017; Rianne, 2017; Urbinello et al., 2014a), and when multiple limits were provided (due to local policies or context), we keep the limit covering the largest population.

2.2.5. *Wi-Fi regulation*

Wi-Fi is a generic term that gathers together a large number of standards covering a wide spectrum of frequencies in the 2.4 GHz and 5 GHz bands. For Wi-Fi, the goal of regulation is to reduce interference by limiting the maximum transmission power. This limit might be different for each country and each frequency. Getting a consolidated view of the various international regulations on Wi-Fi is tricky. For this purpose, we rely on the efforts of J. W. Linville and S. Forshee, who maintain a consolidated file containing the Wi-Fi emitting power per country and frequency for the Linux kernel ("Wireless regulatory database for CRDA" 2021).

To understand the impact of regulation on exposure, we focus on two frequency bands that include a large enough number of countries using different regulations: 2.4 GHz ([2400, 2483] MHz) and 5.3 GHz ([5250, 5350] MHz). The 2.4 GHz (resp. 5.3 GHz) band represents 76% (resp. 2%, still 37 million measurements) of all Wi-Fi measurements. In the 2.4 GHz band, the maximum transmission power is 36 dBm for Australia, 30 dBm for the USA and Canada, and 20 dBm for other considered countries. In the 5.3 GHz band, the maximum transmission power is 24 dBm for Brazil, India, and Canada, 23 dBm for the USA, and 20 dBm for other considered countries.

2.2.6. *Extracting home location*

To accurately identify the home location, we limit our analysis to *dense user* defined as those with at least 14 days of data in a specific month and at least 80% hourly sample density. To calculate sampling density, we count the number of hours between the first and last day we see a user in a given month. An 80% hourly sampling density means that the user has at least one exposure scan for 80% of the counted hours. In our entire dataset, we have 22,907 dense users, which is 9% of all users.

Finally, we use the DBSCAN algorithm (Ester et al., 1996) ($\epsilon = 100$ m, minPts = 24, distance = haversine) on the GPS coordinates of the dense users for each month, independently. We label the cluster that most frequently appears between 10PM and 8AM as the home cluster. All the other clusters are labeled "out-of-home". Therefore, out-of-home gathers together all other indoor and outdoor locations, such as workplace, shopping malls, transportation, or restaurants.

2.2.7. *Statistical conventions*

p-value. We always specify the exact p-value and consider that any p-value below 0.05 represents a statistically significant result.

Boxplot. The boxplot convention used in this paper is the following: the middle box line shows the median, the lower and higher hinges show the first and third quartiles, respectively, and the lower and higher whiskers show a limit of 1.5x the interquartile range from the lower and higher hinges, respectively.

3. Results

3.1. *Evolution of personal exposure from 2017 to 2020*

Table 1 shows the evolution of the total personal exposure in the 13 countries with the largest number of measurements (as discussed in Appendix A.1.3). The overall exposure shows an increasing trend across all countries from 2017 to 2020. To confirm this trend, we computed the Spearman correlation on the monthly average exposure to evaluate the relationship between time (months) and the monthly average exposure for each country. Table 2 shows a significant positive correlation between time and exposure for most countries. We excluded 2020 from this correlation as the COVID-19 period would have significantly impacted the interpretation of this correlation. However, when including 2020, we observed an increase in the Spearman coefficients between 0.1 and 0.2 for most countries and lower p-values for all countries (except CH), showing the impact of lockdowns on exposure. The most significant difference was France, with a Spearman coefficient of 0.42 ($p < 0.01$).

Fig. 1 shows how each wireless technology contributes to this exposure trend. The total exposure (brown curve) has been multiplied by 2.3 (from −34.6 dBm in 2017 to −31 dBm in 2020) over the four-year period. The trend we observe for each wireless technology corresponds to the adoption or decline of the corresponding technology. We observe a clear increase in the exposure due to Wi-Fi and Bluetooth technologies, but a decrease in the exposure due to 2G and 3G technologies. Interestingly, Wi-Fi is by far the largest contributor to exposure.

In summary, we observe an overall increase in total personal exposure

Table 1

Yearly average exposure from 2017 to 2020 in 13 countries. We use an ISO 3166 ("ISO 3166 Country Codes" 2021) alpha-2 country code to represent each country using a two-letter code. We compute the mean and the 95% confidence interval for the mean using empirical bootstrap resampling with replacement (N = 1,000) (Efron and Tibshirani, 1994) on the monthly average exposure for each country. The change column shows the increased (in blue) or decreased (in red) exposure as a percentage compared to the previous year. This percentage change is computed in Watt instead of dBm to have a linear interpretation of the change in exposure.

	2017		2018			2019			2020		
Country	Mean	95%CI	Mean	95%CI	Change	Mean	95%CI	Change	Mean	95%CI	Change
BR	-39.4	[-41.1, -38.1]	-36.3	[-39.1, -34.1]	+105%	-34.4	[-37.3, -32.4]	+56%	-32.0	[-33.1, -31.0]	+71%
AU	-34.2	[-37.4, -31.5]	-34.1	[-36.5, -32.1]	+2%	-31.0	[-34.0, -28.4]	+104%	-31.1	[-31.9, -30.4]	-3%
NL	-39.1	[-41.9, -36.9]	-37.1	[-39.6, -34.9]	+57%	-36.3	[-38.7, -34.3]	+19%	-33.6	[-35.3, -32.1]	+87%
IN	-29.8	[-35.1, -26.3]	-27.6	[-37.0, -23.6]	+64%	-32.2	[-33.8, -30.9]	-65%	-30.6	[-32.2, -29.4]	+46%
ES	-37.4	[-40.2, -35.1]	-35.4	[-37.6, -33.6]	+60%	-32.9	[-34.6, -31.7]	+77%	-31.6	[-32.9, -30.5]	+35%
BE	-40.7	[-42.0, -39.7]	-35.9	[-37.7, -34.3]	+204%	-35.4	[-36.5, -34.4]	+13%	-32.5	[-33.8, -31.5]	+91%
CH	-31.6	[-33.4, -30.2]	-32.9	[-34.4, -31.7]	-25%	-33.1	[-34.9, -31.6]	-6%	-32.6	[-34.3, -31.2]	+13%
GB	-39.2	[-41.0, -37.7]	-34.7	[-36.8, -32.9]	+182%	-32.7	[-35.1, -30.6]	+60%	-30.9	[-32.3, -29.8]	+49%
CA	-35.6	[-37.8, -33.8]	-32.3	[-33.5, -31.0]	+112%	-31.9	[-33.3, -30.6]	+9%	-29.2	[-30.1, -28.3]	+89%
DE	-36.6	[-37.5, -35.9]	-36.9	[-38.4, -35.8]	-7%	-32.8	[-34.8, -31.3]	+158%	-32.1	[-33.0, -31.0]	+19%
IT	-33.8	[-38.4, -30.7]	-33.9	[-35.3, -32.7]	-2%	-33.3	[-34.1, -32.4]	+16%	-32.1	[-33.1, -31.4]	+30%
US	-33.5	[-34.9, -32.0]	-30.5	[-31.2, -29.9]	+98%	-29.8	[-31.0, -28.5]	+18%	-27.3	[-28.3, -26.4]	+76%
FR	-33.5	[-34.1, -33.0]	-33.0	[-33.8, -32.2]	+14%	-33.3	[-33.9, -32.7]	-7%	-31.8	[-32.2, -31.4]	+42%

Table 2
Spearman correlation of the monthly average exposure per country from 01/2017 to 12/2019. In blue, we show the positive correlations, and in red, the negative ones. The grey two-sided p-values are above the threshold of 0.05.

country	BR	AU	NL	IN	ES	BE	CH	GB	CA	DE	IT	US	FR
score	0.44	0.45	0.37	0.14	0.42	0.63	-0.21	0.7	0.57	0.47	0.36	0.62	0.00
p-value	0.0066	0.0058	0.026	0.4	0.011	3.4E-05	0.23	2.2E-06	0.0003	0.0039	0.03	5.8E-05	0.99

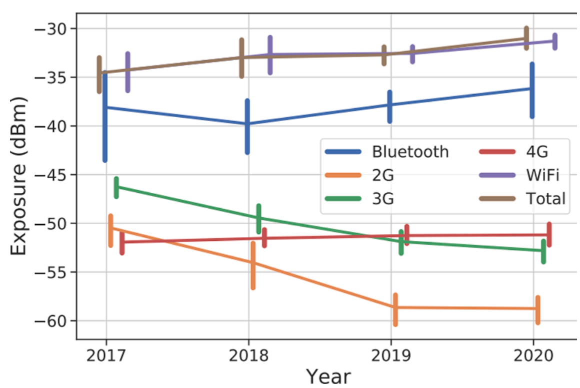

Fig. 1. Yearly average exposure from 2017 to 2020 per wireless technology. For each year, we took the yearly average exposure as given in Table 1, converted it to Watt, computed the mean for all 13 countries, and converted it back to dBm. The bars represent a 95% confidence interval for the mean using empirical bootstrap resampling with replacement (N = 1,000) on the yearly average exposure per country. Plots are shifted horizontally to avoid confidence interval overlap. An increase of 3 dB results in the doubling of the exposure.

with time (a 2.3-fold increase from 2017 to 2020), with Wi-Fi as the largest contributor to personal exposure.

3.2. Impact of individual sources on personal exposure

We focus now on how each source contributes to total exposure. A better understanding of the most exposing sources could inform strategies to reduce personal exposure.

Since the measurement of the number of sources is not reliable for cellular technologies (see Appendix A.1.2 and Appendix A.2.4), we focus on Wi-Fi and Bluetooth technologies. We consider this limitation reasonable because, as shown in Fig. 1, these two are the most largest contributors to total exposure.

Fig. 2 shows the relationship between individual exposure and the number of sources in a vicinity. We observe that beyond four to five sources, additional sources have little influence to individual exposure. This could be explained by the fact that exposure fades with distance in polynomial time (see Eq. (1)). In addition, we see in Fig. 3 that in 50% of the exposure scans, the most exposing Wi-Fi source (resp. Bluetooth) represents at least 83% (resp. 91%) of the total exposure due to Wi-Fi (resp. Bluetooth). Thus, a larger number of sources in the vicinity does not necessarily mean a higher personal exposure; rather, the most exposing source is the primary contributor to exposure.

The question now is how actionable this information is with respect to exposure reduction. We focus on the Wi-Fi-connected sources and Bluetooth-bounded devices to which a user has already connected. Connected sources or bounded devices are usually owned or controlled by the user and can therefore be switched off or moved to reduce exposure. Taking all scans into account, we computed that 41% of the time, the most exposing of all the Wi-Fi sources is a connected one. For Bluetooth, the most exposing source is a bounded device 10% of the

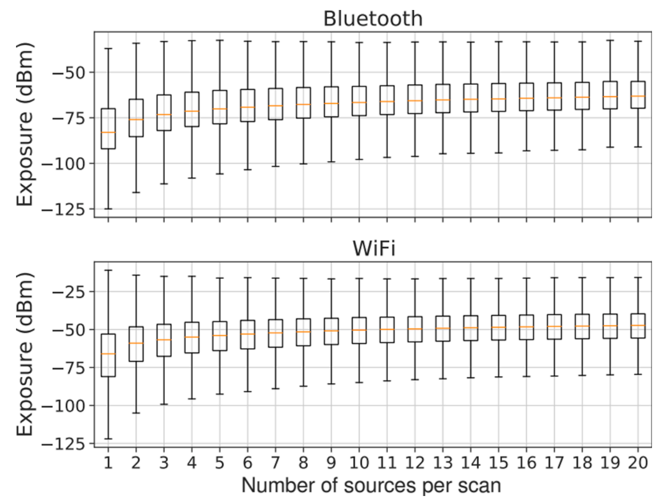

Fig. 2. Correlation between number of sources and exposure to Bluetooth and Wi-Fi. The figure represents the distribution of all the exposure scans in Bluetooth (top) and Wi-Fi (bottom) when there is a given number of (Bluetooth or Wi-Fi) sources in the scan. For instance, the last box in the top figure represents the sum of the received power in Bluetooth for exposure scans with exactly 20 detected Bluetooth sources.

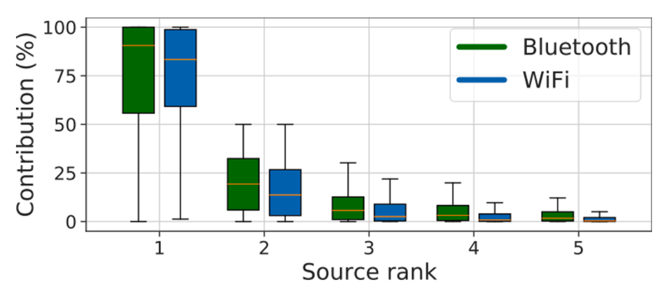

Fig. 3. Distribution of the percentage contribution of the top five exposure sources. This figure represents the distribution of the percentage contribution of the top five exposure sources in all exposure scans, with Bluetooth in green and Wi-Fi in blue. For instance, the first green box shows the distribution of the contribution of the most exposing Bluetooth source to the sum of the exposure of all Bluetooth sources for each exposure scan.

time. Then, we computed what the individual personal exposure would have been if all connected sources and bounded devices had been switched off. While this is an overly optimistic situation, the goal is to assess the degree to which an individual could control exposure. Fig. 4 shows that, by switching off the connected sources and bounded devices, half of the users could have reduced their total exposure by 50% (a reduction by 3.1 dB), and 25% could have reduced their total exposure by 90% (a reduction by 10 dB).

In summary, the growth of total exposure is not explained by an increasing number of sources. On the contrary, a handful of sources generate most of the personal exposure at any given time, and it is not uncommon that

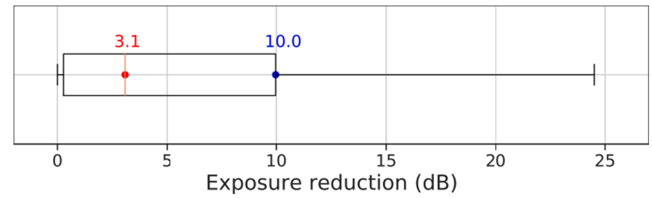

Fig. 4. Distribution of the individual exposure reduction for each user when we remove connected Wi-Fi sources and bounded Bluetooth devices. In red, we show the median and in blue, the 75th percentile. We give details of the computation in Section 2.2.2.

an individual's exposure is almost entirely the result of sources they either own or associate with (for a quarter of our subjects, such sources account for 90% of exposure).

3.3. Impact of regulation on personal exposure

Electromagnetic field emissions are regulated, which means that both the spectrum used and the emitting power per frequency band are fixed by a regulatory authority. The types of cellular and Wi-Fi sources we explore in this paper are regulated on a country-specific basis. Therefore, the maximum emitting power per frequency band is not uniform in the top 13 countries we consider. By contrast, Bluetooth uses the same emitting power in all the countries we consider. We explore next how cellular and Wi-Fi regulations impact the received power.

3.3.1. Cellular regulation

Fig. 5 does not show any clear correlation between regulation limits and exposure. We must be careful interpreting this result as there are several external factors that we do not control, such as the deployment strategy of the cellular operators. For example, operators might decide, in a densely populated area, to have a higher density of base stations (to increase the supported load) emitting at a lower power (to reduce interference). In such cases, base stations expose the population at a level that is significantly lower than what the regulation permits (Urbinello et al., 2014a; Urbinello et al., 2014b). Therefore, in practice, the regulation is an upper bound to the population exposure in some extreme cases, but in most cases, the population is exposed at levels much lower than the regulation limits.

To confirm this hypothesis, we estimated the distribution of the cellular measurements in V/m, because regulation limits are defined for

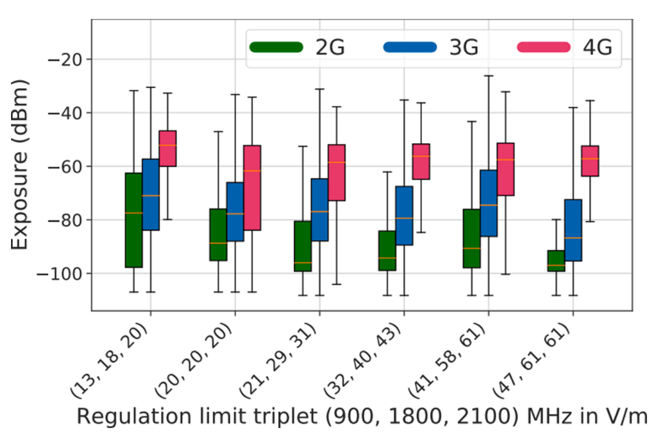

Fig. 5. Correlation between exposure to cellular technologies and regulation limits. This figure shows the correlation between the exposure and a regulation limit triplet for the three cellular technologies we measure, 2G, 3G, and 4G. Here is the association between regulation limit triplets and countries: (13, 18, 20) is for IN; (20, 20, 20) is for IT; (21, 29, 31) is for BE; (32, 40, 43) is for CA; (41, 58, 61) is for FR, DE, GB, CH, ES, NL, AU, BR; (47, 61, 61) is for US. See Section 2.2.4 for details on how we built the triplets.

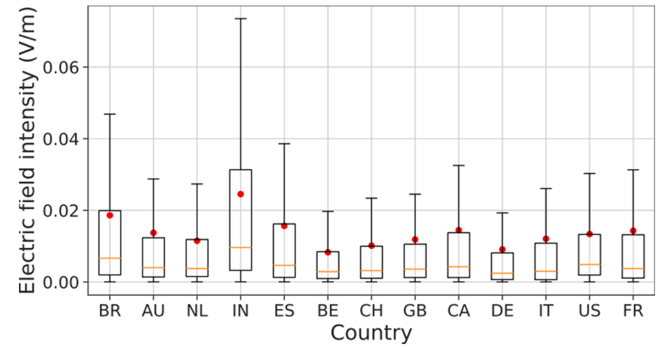

Fig. 6. Per-country distribution of the estimated electric field produced by cellular antennas at the receiver. The red dot shows the mean. Considering all signals together, we have a median at 0.005 V/m, and a 99th percentile at 0.18 V/m.

the electric field that is expressed in V/m (see Section 2.2.3 for details on this estimation).

Fig. 6 shows the distribution of the measured electric field for each exposure scan per country. We see that the current population exposure is orders of magnitude lower than any current regulation limit. We found that by considering all countries together, only 1% of the scans are above 0.18 V/m.

Admittedly, this estimation is a coarse description of reality. We now explore how the different limitations and approximations of our estimation will impact our conclusion. First, the maximum cellular RSSI that we can measure is −51 dBm, so measurements above −51 dBm are capped (see Appendix A.1.2). However, measurements at −51 dBm represent only 1.8% of all measurements, a very small fraction that cannot fundamentally change our conclusions. Second, we applied the same frequency (that of the serving cell) to all cellular measurements in the same exposure scan. Considering that 98% of the frequencies are within [782, 2660] MHz and Eq. (2) is linear with f, we have at most a factor of 3.4. Note that this is a very conservative estimate, as the median frequency is 1,745 MHz. Last, in Boussad et al. (2021), we show, using calibrated measurements in an anechoic chamber, that the average deviation between the real received power at a calibrated isotropic antenna and a smartphone is 2.5 dB. If we translate this offset in Eq. (2), we find that it results in a multiplying factor of $\sqrt{10^{\frac{2.5}{10}}} \approx 1.3$. By combining the two main sources of error, the actual exposure in V/m could be 4.7 times higher than what we report in Fig. 6, which is still orders of magnitude lower than the most restrictive regulation limits in the countries we consider.

In summary, 99% of our exposure scans report a cellular exposure lower than 0.18 V/m (corrected to 0.85 V/m if we take into account the multiplying factor of 4.7, corresponding to a worst-case estimate scenario), which is orders of magnitude lower than any regulation limits in the considered countries.

3.3.2. WiFi regulation

Fig. 7 shows that in the 2.4 GHz band, a transmission (Tx) power of 20 dBm leads to significantly lower exposure than a Tx power higher than 30 dBm. Therefore, this regulation clearly impacts population exposure. Surprisingly, when we observe the exposure for the 5.3 GHz band, we have the opposite result: a Tx power of 20 dBm leads to significantly higher exposure than a Tx power over 23 dBm.

We can explain this seemingly contradictory result. Unlike regulations for cellular, regulations for Wi-Fi limit the Tx power; therefore, it is not surprising to see that Tx power impacts population exposure. When the difference in Tx power is large (a minimum of 10 dB between the two groups in the 2.4 GHz band), the Tx power dominates the other factors that affect population exposure. However, when the difference in the Tx power is small (a maximum of 4 dB for the 5.3 GHz band), other factors

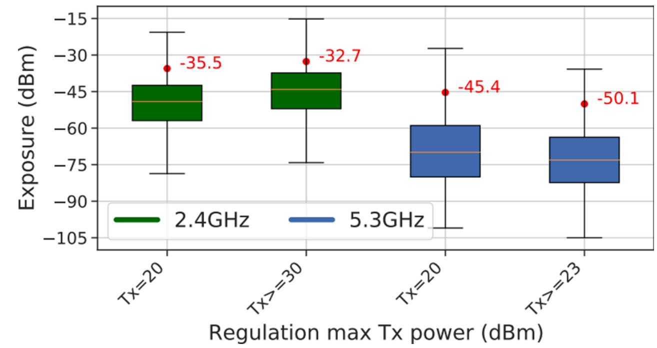

Fig. 7. Correlation between Wi-Fi Tx power and exposure in the 2.4 GHz and 5 GHz bands. The figure shows the distribution of the per-user monthly average exposure using boxplots. The red dot shows the mean. To compute the significance of the mean, we performed a permutation test (N = 1,000,000). The test statistic is the difference of the means for the same frequency band. The two-sided p-value is lower than 0.001 for both bands. See Section 2.2.5 for details on how we define the Tx power.

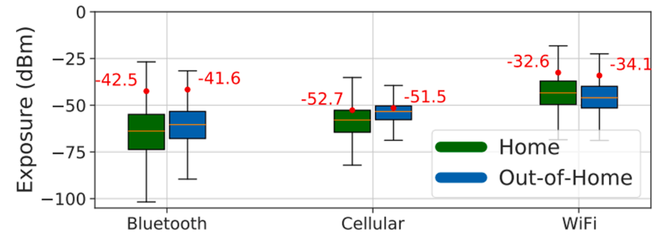

Fig. 8. Correlation between location (home or out-of-home) and exposure for Bluetooth, Cellular, and WiFi. This figure shows the distribution of the per-user monthly average exposure for dense users when they are at home (in green) and out-of-home (in blue) for Bluetooth, Cellular, and Wi-Fi sources. The red dots and labels show the mean exposure. We performed a permutation test (N = 1,000,000) between at-home and out-of-home for each of the three types of sources. We obtained a two-sided $p < 0.001$ for Wi-Fi and Cellular, and a two-sided $p = 0.09$ for Bluetooth.

dominate the population's exposure. Indeed, as the attenuation increases with the frequency (see Eq. (1)), a small 4 dB difference in the Tx power will have a marginal impact on the total exposure compared to, for instance, the deployment and density of Wi-Fi access points per country.

In summary, the impact of Wi-Fi regulation on population exposure depends not only on the Tx power, but also on the frequency bands. It is worth noting that the goal of this regulation is to limit interference rather than population exposure.

3.4. Impact of user location on personal exposure

User location is also a factor that may affect personal exposure. In the following, we focus on two location categories: at-home and out-of-home. The rationale is that, according to the results reported in the previous sections, Wi-Fi is the greatest contributor to total exposure. We hypothesize that users are more exposed at home because most users have Wi-Fi at home[3] and are closer to their router than would be the case in other environments. The goal of this section is to explore the difference between at-home and out-of-home exposure. We detail in Section 2.2.6 how we classify a user at-home or out-of-home.

Fig. 8 shows that users at home are significantly less exposed to cellular radiation (−1.19 dB). The main reason is that cellular antennas are outside, so walls attenuate the radiation. Conversely, exposure to Wi-Fi is higher at home than out-of-home (+1.55 dB). Here, the increased adoption of Wi-Fi technology at home is a reasonable explanation. We computed how many hours (per month) each dense user is connected to a Wi-Fi source at home and out-of-home. We found that half of the users (median) are connected 91% of the time at home, and 29% of the time out-of-home. Finally, we found that the difference of exposure to Bluetooth between at-home and out-of-home is not significant.

In summary, user location has a significant impact on exposure. In particular, users are more exposed to Wi-Fi at home. As they are largely connected to Wi-Fi at home, we further conclude that personal Wi-Fi routers are the most significant factor in at-home exposure.

[3] According to the US Census Bureau, 81% of USA households had internet access in 2016 (US Census 2019). In 2019, more than 80% of the households in the European countries included in our study had internet access, with 83% coverage in France and 98% in the Netherlands) (Eurostat 2020).

4. Discussion

4.1. Position with respect to related works

Understanding the potential human health impacts of exposure to radio frequencies is a long journey. An important challenge in performing sound epidemiological studies is the complexity of characterizing the real exposure of the population. The methods and dataset we present here offer the first analysis of the evolution of radio frequency exposure at population-scale for 13 countries over four years. This change of paradigm from previous small-scale studies (Zeleke et al., 2018; Ramirez-Vazquez et al., 2019, 2021; Bhatt et al., 2018; Birks et al., 2018; Gallastegi et al., 2018; Lahham and Ayyad, 2019) has direct consequences for the current debate on population exposure and the impact of this exposure on health.

Importantly, we do not oppose our work to related works, but argue it comes in complement. Our study allows to raise conclusions with a consistent methodology on a large population during a long period of time. Past works used different methodologies (exposimeters (Velghe et al., 2019; Zeleke et al., 2018; Ramirez-Vazquez et al., 2019), spectrum analyzer (Fernandez et al., 2020), mobile app (Bhatt et al., 2018)) on short period of time (from a few days (Zeleke et al., 2018; Ramirez-Vazquez et al., 2019) to a few months (Urbinello et al., 2014b; Aerts et al., 2018)) for a small population (from a few tens (Velghe et al., 2019; Zeleke et al., 2018; Ramirez-Vazquez et al., 2019) to a few hundreds (Birks et al., 2018; Breckenkamp et al., 2012)). Whereas such works are important, they are hard to compare due to a large variety in terms of methodologies and cohorts. Our work provides a benchmark to understand how location and time period might impact past studies. In addition, the cited small-scale studies performed with exposimeters or spectrum analyzers are extremely useful because they are more accurate than smartphones, and have a broader spectrum coverage. Therefore, we argue that both small scale studies using exposimeters and large-scale studies using smartphones are useful and complement each other to have a better understanding of the population exposure.

In addition, our work confirms findings in previous studies: people are more exposed at home to Wi-Fi (Lahham and Ayyad, 2019), Wi-Fi 2.4 GHz is more exposing than Wi-Fi 5 GHz (Ramirez-Vazquez et al., 2021), exposure levels to cellular radio frequencies are orders of magnitude lower than the regulatory limits (Urbinello et al., 2014a; Ramirez-Vazquez et al., 2019; Gajšek et al., 2015; Sagar et al., 2018b; Lahham and Ayyad, 2019), indoor exposure (mainly caused by Wi-Fi) increases at a higher rate than outdoor exposure (mainly caused by cellular) (Gajšek et al., 2015), Wi-Fi is the main contributor to population exposure (Lahham and Ayyad, 2019; Breckenkamp et al., 2012)

However, some related works found that cellular downlink is the main source of exposure (Zeleke et al., 2018; Bhatt et al., 2017; Ramirez-Vazquez et al., 2019; Birks et al., 2018; Gallastegi et al., 2018). All of these studies consider a small population sample (from 10 to 529 persons) during a very short duration (1 to 3 days). In addition, they all suffer from a recruitment bias: three studies considered participants from a single big city, two studies focused solely on children. Whereas these studies bring important elements to understand exposure on specific context and population, they cannot be generalized.

We showed (Boussad et al., 2021) using controlled experiments with calibrated professional spectrometers that our approach based on measurements with the ElectroSmart app is accurate enough for our analysis. The main and unique contribution of our work is to provide with a same methodology a unified view of exposure for a large population on 13 countries during 4 years.

4.2. Main study implications

Our solid methodology and population coverage permit to shed a new light on two important debates. First, the Council of Europe, following the principle of precaution, has called for an *As Low As Reasonably Achievable* (ALARA) rule (European Parliamentary Assembly, 2011). In line with this principle, one proposal is to reduce exposure levels as low as 0.6 V/m and even 0.2 V/m in the medium term. The debate currently includes proponents, who see ALARA as a necessary drastic reduction to curb the current level of exposure, and cellular operators, who oppose ALARA by arguing that it would impede the deployment of communication infrastructure, and thus, eventually, access. We reveal that for the vast majority of the population, exposure is already below the lowest ALARA level. However, reducing the current regulation levels would still benefit the small fraction of the population that is currently more exposed than recommended by the ALARA rule.

Second, our work also fundamentally changes the debate on frequency exposure, currently heavily centered on the regulation of cellular operators. Not only do we show that Wi-Fi is by far the largest contributor to population exposure, but also that a few sets of sources, namely those used by individuals and those present at home, are the key contributors. Offering tools for individuals to prevent unnecessary exposure at home, or working on technology that automatically reduces exposure are just some examples of short and medium term ways to expand the precautionary principle. Such approaches have not yet received the attention that they deserve.

Beyond these direct implications, we envision our work and dataset providing a foundation for future epidemiological studies. Upon publication, all data used in this paper will be available online for scientific exploitation. The data consists of timestamped measurements of RSSI for each of the five types of signals considered in this paper (Wi-Fi, Bluetooth, 2G, 3G, 4G). All user IDs have been anonymized (using a salted hash), and all GPS locations have been replaced by one of the 13 countries we consider. When required to preserve user anonymity, we provide aggregated data using pre-processing steps. For instance, we provide the identification of the unique physical sources using our own anonymous source counter. A detailed description of the format of the data will be available on the online publication site upon publication.

4.3. Limitations

We performed all scans with a vanilla version of Android using the regular Android API. That is, we did not have access to low-level data available from rooted smartphones or customized drivers. This approach is beneficial for targeting a large-scale audience, but it limits what we can measure, as elaborated below.

First, we only measured the downlink received by the measuring smartphone. Therefore, the contribution of the uplink to the exposure, that is, the emission of the measuring smartphone, is not considered in this study. Also, we did not measure the uplink of surrounding devices. This is an important limitation, but we are not aware of any technical solution to measure the uplink at scale. We argue that having a consistent view of the downlink at scale is already an important and significant step forward.

Second, the minimum and maximum measurable power for each wireless technology is capped by the Android API and the technology standards. We show in Table 3 the valid ranges of measurements for each technology. For example, if a smartphone is exposed to a higher power than the maximum measurable power, it will always report the maximum value presented in Table 3. We explain in Appendix A.1.2 how we filtered out-of-range scans, and show that valid out-of-range scans represent of small fraction that cannot fundamentally change our conclusions.

Third, for 2G, 3G, and 4G, the RSSI is provided by the Android API as an *Arbitrary Strength Unit* (ASU), an integer value between 0 and 31. It is converted to dBm according to the formula: $dBm = ASU*2 - 113$. For this reason, the granularity of the cellular RSSI is 2 dB.

Fourth, each wireless technology comes with some additional limitations. Bluetooth sources can only be measured when they are *discoverable*. Wi-Fi sources can only be measured when they are configured as access points, that is, the emitting power of the connected devices is not measured. Measurements of cellular sources suffer from several limitations. i) A smartphone with an active SIM card can only measure the RSSI from the operators declared in the SIM card. We explain in Appendix A.2.4 how we mitigate this issue. ii) The measurement coverage is largely dependent on the version of Android and the cell phone maker. Indeed, the Android API can return the RSSI of the serving cell for all smartphones, but only the most recent versions of Android can also return the neighboring cells' RSSI. In addition, this API tends to be quite buggy due to the Android RIL (Radio Interface Layer, which is closed-source and vendor-specific. In particular, some smartphones return invalid RSSI measurements (outside of the range given in Table 3). We discuss in Appendix A.1 how we identified and removed invalid measurements. iii) Smartphones periodically scan for cellular networks to ensure continuity of service. To speed up network scanning, smartphones follow priority rules that are defined by the network and stored in the SIM card. This means that a given smartphone may not scan for all the cellular Radio Access Technology (RAT), but instead, scan only high priority RATs. For example it may scan only 4G and 3G networks, excluding 2G. As a result, we expect the cellular scans not to include all the cellular generations in a single scan.

Fifth, the received power was measured using the Received Signal Strength Indicator (RSSI). Therefore, our measurements do not take into account the effective load of the wireless channel.

Last, ElectroSmart can only measure radio frequencies produced by Wi-Fi access points, Bluetooth devices and cell towers. It does not measure radio frequencies emitted by other sources such as FM radio or TV, which are two important sources of radio frequencies that might dominate all other sources in some places. We argue this limitation is acceptable for the following reasons. They operate in a radio frequency lower than microwaves, have a quite static deployment compared to the sources we consider in this work, and have been present for more than 60 years. In contrast, Wi-Fi access points, Bluetooth devices, and cell tower deployment has been dramatically increasing in the past 20 years. Therefore, this significant increased exposure to a frequency band not present before poses questions.

5. Conclusion

In this paper, we presented the largest crowd-based measurement of population exposure to RF produced by cellular antennas, Wi-Fi access points, and Bluetooth devices for 254,410 unique users in 13 countries from January 2017 to December 2020. We showcased the strength of using crowdsource data from mobile smartphones in performing a large-scale and long-term assessment of population exposure to RF radiations. This enabled us to assess the impact of various factors on the exposure using a uniform methodology, which facilitates cross-population and cross-environment analysis. We showed that total exposure has been multiplied by 2.3 in the four-year period considered, with Wi-Fi as the largest contributor. The cellular exposure levels are orders of magnitude lower than regulation limits and are not correlated to national regulation policies. The population tends to be more exposed at home; for half of the study subjects, personal Wi-Fi routers and Bluetooth devices contributed to more than 50% of their total exposure.

An interesting next step would be to consider how the deployment of 5G impacts population exposure. Indeed, in this study, we did not consider 5G as its deployment in the considered countries was small and few smartphones supported 5G before 2021. 5G comes with its own challenges for the evaluation of exposure: it uses small cells, millimeter waves, and beam forming, which changes exposure during transmission. This will undoubtedly be a challenge to correctly characterize exposure to 5G.

CRediT authorship contribution statement

Yanis Boussad: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Xi (Leslie) Chen:** Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Arnaud Legout:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Augustin Chaintreau:** Conceptualization, Formal analysis, Methodology, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Walid Dabbous:** Writing – original draft, Writing – review & editing.

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 material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2022.107144.

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