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# Longitudinal Study of Exposure to Radio Frequencies at Population Scale

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## Abstract

Evaluating population-scale exposure to the radio frequencies (RF) used in wireless telecommunication technologies is important for conducting sound epidemiological studies on the health impacts of these RF [1, 2]. Numerous studies have reported population exposure, but have used very small population samples. In this context, the real exposure of the population to RF remains subject to controversy [3, 4, 5, 6]. 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. All measurements were obtained from the ElectroSmart Android app [7], and we applied a thorough methodology to clean and consolidate the measurements. 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 the regulation limits and not significantly impacted by national regulation policies. Therefore, the mere comparison of exposure levels to regulation limits is a poor way to describe the real evolution of exposure. 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. We make our dataset publicly available to provide a starting point for sound epidemiological studies on the health impacts of RF, and for other types of studies interested in population exposure to RF or the usage of wireless communication technologies.

*Keywords:* radiofrequency, population exposure, crowdsourcing, personal measurements, large-scale

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## 1. Introduction

The long-term impact of radio frequencies on health is a long-standing scientific question that is well illustrated by the classification of radio frequencies as a Group 2B carcinogen by the WHO [8]. This classification means that *there is some evidence that it can cause cancer in humans but at present it is far from conclusive*[9]. Total exposure to various sources of radio frequencies is considered a critical factor for

mitigating health hazards, but in the wild, this exposure varies greatly with time and among individuals. Environmental and behavioral factors play a role, as previous assessments have shown[10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26], limiting the generalizability of results obtained from small study-groups or sparsely instrumented measurements. We present here the first longitudinal analysis of exposure events on a large subject population; results span four years, from approximately a quarter-million unique subjects in 13 countries across Europe, the Americas, Asia, and Australia. The scale of our study allows us to offer the first generalizable findings on critical epidemiological questions regard-

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24 ing the growth of radio exposure worldwide and the  
25 respective contributions of different technologies to  
26 this growth. We also consider the effectiveness of reg-  
27 ulation and some of the factors within an individual’s  
28 control that affect exposure. Beyond these advances,  
29 the release of our data (in a form rendering users  
30 unidentifiable) can facilitate large-scale epidemiolog-  
31 ical studies on the impact of radio frequencies. The  
32 data were collected using the crowdsourcing Android  
33 app ElectroSmart [7] that we developed to instrument  
34 a smartphone’s baseband and report Received Sig-  
35 nal Strength Indicators (RSSI) for radio frequencies  
36 received from cellular infrastructures, Wi-Fi access  
37 points, and Bluetooth devices. Our dataset includes  
38 the exposure of 254,410 unique persons from January  
39 2017 to December 2020.

## 40 2. Materials and Methods

41 This study relies heavily on the quality of the data  
42 we collected. In this section, we present our data  
43 collection methodology, the dataset we collected, and  
44 the cleaning we applied to this dataset.

### 45 2.1. Data collection

#### 46 2.1.1. The ElectroSmart measurement app

47 ElectroSmart [7] is an Android consumer app we  
48 designed to measure the power that a given smart-  
49 phone receives from Wi-Fi access points, Bluetooth  
50 devices, and cell towers. To reach a large audience,  
51 we put a great deal of effort into the user experience,  
52 designing ElectroSmart to be an easy-to-use tool that  
53 offers users transparent information on their exposure  
54 to radio frequencies. ElectroSmart can be installed  
55 on any Android smartphone running Android 4.1 or  
56 later. The app was first launched in August 2016,  
57 and as of May 18<sup>th</sup>, 2021, it had 900,000 downloads  
58 and 190,000 active users.

59 ElectroSmart performs an *exposure scan* every 20  
60 minutes when used in the background. All scans are  
61 periodically collected on our servers. Below, we ex-  
62 plain how an exposure scan works and describe the  
63 information it collects. We discuss user consent and  
64 privacy protection in the following section. A scan  
65 performs the following actions.

- It creates a timestamp with the local time in 66  
UTC. This is a slight approximation as signals 67  
might not be measured at exactly the same time 68  
in a given measurement scan. However, by con- 69  
sidering a window of a few seconds, it is easy to 70  
attribute all measured signals to a given mea- 71  
surement scan and timestamp (we specifically 72  
discuss the case of Bluetooth in the section *Blue- 73  
tooth scan synchronization*). 74
- It collects characteristics of the smartphone 75  
(brand and model) and its Android version. 76
- It measures the smartphone location in terms of 77  
latitude and longitude. Android provides this 78  
information by combining GPS, Wi-Fi access 79  
points, and cell tower information using a pro- 80  
prietary algorithm. 81
- It measures the *downlink* Received Signal 82  
Strength Indicator (RSSI) of all measurable Wi- 83  
Fi access points, Bluetooth devices, and cell tow- 84  
ers (we discuss limitations below), along with 85  
several source-specific data. 86
  - For Wi-Fi access points, we collect the 87  
SSID, the BSSID, the frequency, and 88  
whether the user is connected to this access 89  
point. 90
  - For Bluetooth devices, we collect the de- 91  
vice name, the device MAC address, and 92  
whether the user is bonded to this device. 93
  - For cell towers, we identify whether the cell 94  
is using a 2G, 3G, 4G, or CDMA/EVDO 95  
technology. We determine whether the cell 96  
is serving (that is, the user is currently 97  
connected to this cell), and we collect cell 98  
identification information, such as the Mo- 99  
bile Network Code (MNC), Mobile Country 100  
Code (MCC), or Cell ID (CID), to generate 101  
a unique identity for each cell tower. 102

#### 103 2.1.2. Ethical and legal considerations

104 We submitted the study protocol to our institu-  
105 tional ethical committee (Inria COERLE [27]). They  
106 provided guidelines for respecting user privacy, con-  
107 sent, and data protection.

	WiFi	Bluetooth	Cellular (2G, 3G, 4G)
Max	-1	-1	-51
Min	-126	-150	-113

Table 1: **Valid range of the RSSI (in dBm) for each wireless protocol.**

ElectroSmart requires explicit user consent for all information collection. In particular, we are fully compliant with the European General Data Protection Regulation (GDPR) [28].

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.

### 2.1.3. Limitations

We perform all scans with a vanilla version of Android using the regular Android API. That is, we do 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 measure 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 do not measure the uplink of surrounding devices.

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 1 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 1. We explain in *Dataset Cleaning* how we filter out-of-range scans.

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:  $\text{dBm} = \text{ASU} * 2 - 113$ . 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. In practice, it is either the cellular operator that owns the SIM card (MNO), the cellular operator that is operating the cellular infrastructure for the virtual operator (MVNO), or the operators that partner with the MNO of the SIM card in foreign countries (Roaming). We explain in the *Dataset Processing* section 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 1). We discuss in *Dataset Cleaning* how we identify and remove 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.

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

## 2.2. Dataset characteristics

In this study, we use all the exposure scans collected from January 2017 to December 2020 (4 years) representing 506,100 user profiles and 6,438 million measured RSSI.

We first clean this raw dataset as follows: i) we remove all measurements with invalid GPS coordinates, ii) we remove all measurements with invalid RSSI values, iii) we keep only measurements from the 13 countries with the largest number of measurements, iv) we remove all CDMA/EVDO measurements.

Then, we process the remaining measurements: v) we convert all timestamps to the local time of the country of origin, vi) we identify the Wi-Fi physical sources, vii) we attribute each Bluetooth measurement to an atomic scan. The following sections detail each of these seven steps.

### 2.2.1. Dataset cleaning

*Invalid GPS coordinates removal.* Background measurements are quite fast (typically a few seconds). There is usually not enough time to get a valid GPS coordinate from scratch, that is, when the GPS was not activated before the scan or when no prior information is cached to help the GPS converge faster to a location. However, location is a system-wide property, so if another app or the system has recently accessed the device location, we will benefit from this when we make the scan. Also, when the device is not power-constrained, we can allow more time to get a valid GPS location.

When a GPS coordinate cannot be retrieved in the ElectroSmart app, we set both the latitude and the longitude associated with a scan to either 0 or -1 depending on the root cause (in this paper, we do not exploit this root cause). As one of our goals is to explore the evolution of the exposure per country, we removed all scans with a GPS coordinate set to either 0 or -1. We removed 7.9% of the Wi-Fi measurements, 9% of the Bluetooth measurements, 18.2% of the 2G measurements, 19.8% of the 3G measurements, and 12.8% of the 4G measurements. Overall, we removed 11.2% of all the raw measurements by filtering out invalid GPS coordinates.

*Invalid RSSI removal.* The Android OS is an open-source software program that is common to all Android devices, but each smartphone manufacturer adapts it to their hardware by performing customization and developing drivers, all of which are proprietary. Therefore, each smartphone model can come with specific bugs [29]. This step focuses on the RSSI, which is produced by the proprietary Radio Interface Layer (RIL).

Fortunately, each wireless standard comes with a valid range for the RSSI value, as shown in Table 1. We can therefore easily filter out each measurement with an out-of-range RSSI value. We removed 0.07% of the Wi-Fi measurements, 0.04% of the Bluetooth measurements, 0.8% of the 2G measurements, 2.4% of the 3G measurements, and 14.1% of the 4G measurements. After this removal step, 85.9% of all the raw measurements remained.

In addition to the out-of-range values, we also observed in-range abnormal values for cellular measurements (2G, 3G, 4G). Abnormal values are in the valid range but tend to appear with higher frequency in the same *exposure scan*. The root cause of these abnormal values is hard to pinpoint as it most likely comes from bugs in the proprietary RIL. In particular, we observed that all smartphones with an Exynos [30] System on Chip (SoC)<sup>1</sup> have an abnormally high number of -51 dBm measurements: for all cellular measurements performed from smartphones with an Exynos SoC, the -51 dBm values represent 71% of all cellular measurements, whereas, they represent 1.91% for all smartphones running any SoC other than Exynos.

We found that the cells reporting abnormal values correspond to fake cells, that is, when the RIL reports a cell, but it does not correspond to a real measured cell. Indeed, when a smartphone connects to a cellular operator, it measures various performance indicators (including the RSSI), and connects to the cell with the best performance indicator; we call this cell the *-serving cell*. All the other cells are called *neigh-*

<sup>1</sup>Most likely, the issue comes from the modem associated with the Exynos SoC, but we only have access to the SoC name from the Android API.

275 *boring cells*. We found that for 3G, the percentage of  
276 neighboring cells measured by smartphones with an  
277 Exynos SoC is 21.8% of all measured cells, whereas it  
278 is 2.7% for smartphones running any SoC other than  
279 Exynos. This is a clear indication that smartphones  
280 with an Exynos SoC report fake neighboring cells, at  
281 least for 3G.

282 Due to the bogus behavior of smartphones run-  
283 ning an Exynos SoC, we decided to adopt a conser-  
284 vative strategy by removing all measurements (Wi-  
285 Fi, Bluetooth, 2G, 3G, 4G) performed by a smart-  
286 phone with an Exynos SoC. Even if the issue does  
287 not concern Wi-Fi and Bluetooth, removing only cel-  
288 lular measurements (while keeping Wi-Fi and Blue-  
289 tooth measurements) would have affected our discus-  
290 sion of personal exposure by changing the proportion  
291 of the sources of exposure. We removed 24.4% of the  
292 Wi-Fi measurements, 33.5% of the Bluetooth mea-  
293 surements, 7.9% of the 2G measurements, 40.6% of  
294 the 3G measurements, and 10.8% of the 4G mea-  
295 surements. After this removal step, 62.6% of all raw  
296 measurements remained.

297 For the sake of completeness, we note that we also  
298 observed an abnormally large number of measure-  
299 ments with a -113 dBm RSSI for 2G and, to a lesser  
300 extent, for 3G. We did not, however, find any corre-  
301 lation between these -113 dBm measurements and a  
302 specific SoC, device brand, or Android version. As  
303 dBm are in a logarithmic scale, and since we perform  
304 all our computations in Watt, which is in a linear  
305 scale, the impact of these measurements on the rest  
306 of this paper is negligible.

307 *Included countries*. ElectroSmart was released in Au-  
308 gust 2016 in two languages, English and French.  
309 We added Italian and German in March 2019, and  
310 Spanish and Portuguese in January 2020. France  
311 is the country with the largest number of measure-  
312 ments (36% of all measurements after removing in-  
313 valid GPS and RSSI), followed by the USA (27.5%),  
314 Italy (7.9%), and Germany (4.6%).

315 We restricted this study to the 13 countries with  
316 the largest number of measurements. In addition to  
317 France, the USA, Italy, and Germany, we included (in  
318 order from the highest to the lowest number of mea-  
319 surements) Canada, the United Kingdom, Switzer-

land, Belgium, Spain, the Netherlands, India, Aus- 320  
321 tralia, and Brazil. Although Brazil accounts for only  
322 0.5% of all measurements, this still represents 21.6  
323 million measurements and 2668 unique users.

324 Altogether, the excluded countries represent 9.3%  
325 of all measurements. So, after this step, 56.8% of  
326 all raw measurements and 50.3% of all user profiles  
327 remained.

328 *CDMA removal*. The term CDMA refers to a large  
329 family of cellular protocols (cdmaOne, CDMA2000,  
330 EVDO) deployed mainly in North America. Elec-  
331 troSmart can measure CDMA cells, but, apart from  
332 in the USA, we did not find CDMA measurements  
333 in any of the selected countries. In the USA, all  
334 CDMA measurements represent 0.95% of all cellu-  
335 lar measurements (4G measurements represent 64%  
336 of all cellular measurements). As CDMA measure-  
337 ments are only used in the USA in our filtered dataset  
338 and represent a negligible fraction of all cellular mea-  
339 surements, we decided to remove all CDMA measure-  
340 ments from our dataset.

341 *Cleaned dataset characteristics*. In the rest of  
342 this paper, we will only refer to the cleaned dataset  
343 that resulted from the previous removal steps. This  
344 dataset contains 254,410 user profiles and 3,656 mil-  
345 lion measured RSSI. This represents 56.8% of all the  
346 measurements and 50.3% of all the profiles available  
347 in the raw dataset.

348 In this cleaned dataset, Wi-Fi represents 58.3% of  
349 all measured RSSI, Bluetooth 6.6%, 2G 10.5%, 3G  
350 7.6%, and 4G 17%.

### 351 2.2.2. Dataset processing

352 *Adapting to local time*. All the raw measurements in  
353 the dataset are associated with a timestamp in UTC  
354 that corresponds to the instant the corresponding sig-  
355 nal was detected. In order to identify day and night  
356 periods, we need to convert all timestamps into local  
357 time. To do so, we reverse-geocode the GPS coordi-  
358 nate of each measurement using OpenStreetMap’s  
359 Nominatim [31] to determine the corresponding coun-  
360 try. Then we convert the timestamp in UTC to a  
361 timestamp in the local timezone of the GPS coordi-  
362 nate using `timezonefinder` python library [32].

363 *Identifying physical and logical WiFi sources.* Identifying  
364 the physical sources of radio frequencies is par-  
365 ticularly important for assessing exposure. This no-  
366 tion of physical source can be tricky. In this paper, a  
367 physical source is the source of a carrier signal, that  
368 is, the source of a signal at a specific frequency. For  
369 Bluetooth, 2G, 3G, and 4G, one detected signal cor-  
370 responds to one physical source, but this is not the  
371 case for Wi-Fi.

372 A Wi-Fi access point usually has one or two phys-  
373 ical sources of emission, but the signals we measure  
374 correspond to logical sources, and it is common to  
375 have multiple logical sources for one physical source.  
376 We can obtain the carrier signal frequency for each  
377 measured source, and one might argue that this in-  
378 formation is enough to identify the physical sources.  
379 However, it is not the case, as different physical  
380 sources can use the same frequency. This is a com-  
381 mon issue in Wi-Fi as the number of available fre-  
382 quencies (called channels) is limited, and the density  
383 of sources is high.

384 Wi-Fi networks are based on the notion of a ser-  
385 vice set, that is, the idea that logical networks can  
386 be layered on top of a physical network. Such logical  
387 networks are identified by a Service Set ID (SSID)  
388 (usually a human-readable string) associated with a  
389 Basic Service Set ID (BSSID), which is a 6-byte, in-  
390 ternationally unique identifier usually derived from  
391 the MAC address of the access point. The strategy  
392 used to derive a BSSID from a MAC address depends  
393 on the equipment and administrator. We observed  
394 three strategies: the BSSID differs from the MAC  
395 address by the first byte, the last byte, or both the  
396 first and last bytes.

397 Therefore, the rule we apply to identify a physical  
398 source in a user scan is the following: if several Wi-Fi  
399 measurements report the same frequency and have  
400 the same BSSID (excluding the first and last bytes  
401 in the comparison), we associate them to the same  
402 physical source. In addition, as logical sources for  
403 the same physical source might report different RSSI  
404 (because the measurements might not be performed  
405 at the exact same time), we consider that the RSSI  
406 of the physical source is the maximum RSSI of all the  
407 associated logical sources for a given scan.

408 In the rest of this paper, all results we report for

Wi-Fi are for physical sources. 409

*Bluetooth scan synchronization.* When counting the  
410 number of sources, it is important to use the concept  
411 of an atomic scan, that is, a scan that reflects the  
412 instantaneous exposure as measured by the smart-  
413 phone. Cellular and Wi-Fi scans are atomic because  
414 the Android API returns all current sources in a sin-  
415 gle call or callback. However, this is not the case  
416 for Bluetooth. When we start a Bluetooth scan, the  
417 smartphone will perform a Bluetooth inquiry request  
418 and wait for an answer from devices in the vicini-  
419 ty [33]. Therefore, devices will reply one by one,  
420 usually within 15 seconds of the start of the scan. 421

The heuristic we use to attribute replying devices  
422 to an atomic scan is to group together all Bluetooth  
423 devices whose inter-arrival is less than 15 seconds. 424

In the rest of this paper, each time we count the  
425 number of Bluetooth devices, we count the number of  
426 devices in an atomic scan as defined in this section. 427

*Mitigation of the cellular scans limited to the SIM op-*  
428 *erator.* We have explained in the *Limitations* section  
429 that the cellular measurements only take into account  
430 the RSSI from the operator declared in the SIM card.  
431 This limitation results in a significant underestima-  
432 tion of the cellular exposure. To mitigate this issue,  
433 in each scan, we multiple the RSSI corresponding to  
434 a cellular measurement with the number of operators  
435 in the country in which the scan was performed. 436

### 2.3. Personal exposure definition and calculation 437

We define personal exposure as the received power  
438 from all the electromagnetic field sources on the ra-  
439 dio frequency bands exposing humans. The received  
440 power is a function of the emitting power that is  
441 expressed in Equation (1) where  $P_r$  is the received  
442 power,  $P_e$  is the emitting power,  $K$  is a constant  
443 dependant on the emitting and receiving antennas'  
444 characteristics,  $d$  is the distance to the source, and  $f$   
445 is the signal frequency [34]. We see in Equation (1)  
446 that distance plays an important role in personal ex-  
447 posure, as does signal frequency: higher frequency  
448 signals fade faster than lower ones. 449

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

450 The analysis we perform in this paper is based on  
 451 three main calculation steps that we describe and justify  
 452 in the following. i) First, for all computations  
 453 based on an exposure scan (as defined in Materials  
 454 and Methods), we consider the sum of the received  
 455 power in Watt of all signals in this scan. Computing  
 456 the sum is relevant because an exposure scan is  
 457 atomic in terms of time, so it represents all the signals  
 458 simultaneously exposing an individual. ii) Second, we  
 459 average the exposure scans of each user per month.  
 460 This gives a per-user monthly average exposure. The  
 461 rationale of computing per-user monthly averages is  
 462 to prevent users with a large number of measurements  
 463 from biasing the monthly average. iii) Third, for each  
 464 country, we group the per-user monthly average exposures.  
 465 When a user has been in different countries for a given  
 466 month, we compute one monthly average exposure per  
 467 country. Then, we compute the mean of these per-user  
 468 monthly average exposures to obtain a monthly average  
 469 exposure per country. Finally, we obtain the yearly  
 470 average exposure by computing the mean of the monthly  
 471 average exposure per country. Computing the yearly  
 472 average exposure this way avoids bias that could be  
 473 introduced by months with a larger than average  
 474 number of users.

#### 475 2.4. Data availability

476 Upon publication, all data used in this paper will  
 477 be available online for scientific exploitation. The  
 478 data consists of timestamped measurements of RSSI  
 479 for each of the five types of signals considered in  
 480 this paper (Wi-Fi, Bluetooth, 2G, 3G, 4G). All user  
 481 IDs have been anonymized (using a salted hash), and  
 482 all GPS locations have been replaced by one of the  
 483 13 countries we consider. When required to preserve  
 484 user anonymity, we provide aggregated data using  
 485 pre-processing steps. For instance, we provide the  
 486 identification of the unique physical sources using  
 487 our own anonymous source counter. A detailed  
 488 description of the format of the data will be available

on the online publication site.

### 3. Results

#### 3.1. World-wide sustained growth of radio exposure is primarily driven by WiFi

Table 2 shows the evolution of the total personal exposure in the 13 countries with the largest number of measurements (as discussed in Materials and Methods). We observe an overall trend of increased exposure 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 3 shows a significant positive correlation between time and exposure for most countries.

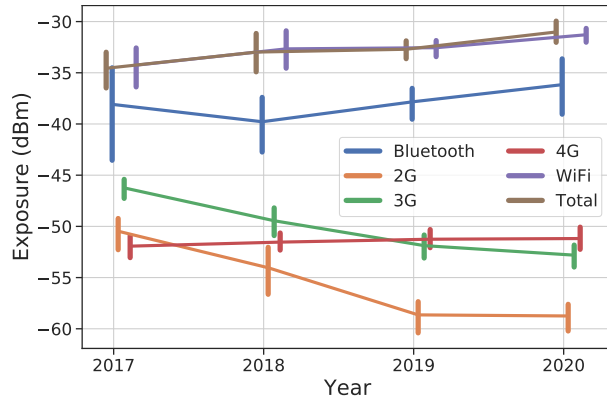


Figure 1: **The total exposure of the population has been multiplied by 2.3 in 4 years.** For each year, we take the yearly average exposure as given in Table 2, convert it to Watt, compute the mean for all 13 countries, and convert it back to dBm. The bars represent a 95% confidence interval for the 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.

It is interesting to understand how each wireless technology contributes to this exposure trend. Figure 1 shows that 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



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

Table 2: **The yearly average exposure increased from 2017 to 2020 worldwide.** This table represents the evolution of the yearly average exposure per country. We use an ISO 3166 [35] 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) [36] 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.

510 we observe for each wireless technology corresponds  
511 to the adoption or decline of the corresponding tech-  
512 nology. We observe a clear increase in the exposure  
513 due to Wi-Fi and Bluetooth technologies, but a de-  
514 crease in the exposure due to 2G and 3G technologies.  
515 Interestingly, Wi-Fi is by far the largest contributor  
516 to exposure.

517 *In summary, we observe an overall increase in total*  
518 *personal exposure with time (a 2.3-fold increase from*  
519 *2017 to 2020), with Wi-Fi being the largest contribu-*  
520 *tor to personal exposure.*

### 521 3.2. Exposure growth is not explained by the multi- 522 plication of sources

523 We focus now on how each source contributes to  
524 total exposure. This is a central question because an  
525 improved understanding of the most exposing sources  
526 could inform strategies for reducing personal expo-  
527 sure.

528 Since the measurement of the number of sources  
529 is not reliable for cellular technologies (see Materi-  
530 als and Methods), we focus on Wi-Fi and Bluetooth  
531 technologies. We consider this limitation reasonable

because, as shown in Figure 1, these two are the most  
532 significant contributors to total exposure. 533

Table 3: **The Spearman correlation shows a significant positive correlation between time and exposure for most countries.** The Spearman correlation is computed on the monthly averages for each country from 01/2017 to 12/2019. We exclude 2020 from this correlation as the COVID-19 period would have significantly impacted the interpretation of this correlation. 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. When including 2020, we observe 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 is France, with a Spearman coefficient of 0.42 (p<0.01).

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

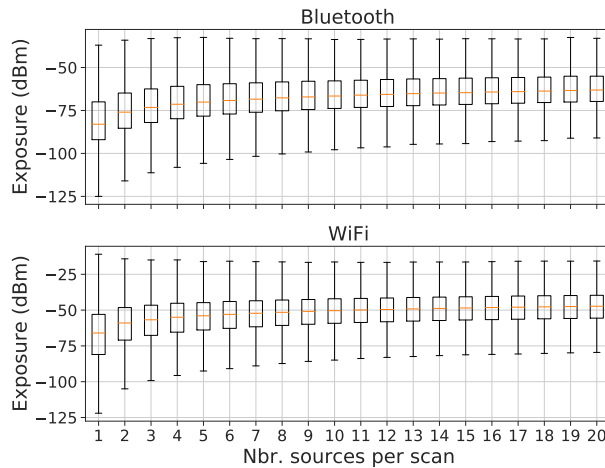


Figure 2: **A large number of sources in the vicinity marginally increases individual exposure.** The figure represents the distribution of all the exposure scans in Bluetooth (top) and Wi-Fi (bottom) when there is a given number of (Bluetooth or Wi-Fi) sources in the scan (the boxplot convention is the following: the middle orange 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). 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. We observe that beyond 4 to 5 sources in the vicinity, any additional sources marginally change the individual exposure.

534 Figure 2 shows the relationship between individual  
 535 exposure and the number of sources in a vicinity.  
 536 We observe that beyond four to five sources, additional  
 537 sources do not significantly increase individual  
 538 exposure. Although this finding might seem counter-  
 539 intuitive, it is mainly explained by the important fading  
 540 with the distance of the electromagnetic fields  
 541 (see Equation 1). In addition, we see in Figure 3  
 542 that in 50% of the exposure scans, the most exposing  
 543 Wi-Fi source (resp. Bluetooth) represents at least  
 544 83% (resp. 91%) of the total exposure due to Wi-Fi  
 545 (resp. Bluetooth). Thus, the number of sources in  
 546 the vicinity is not a good predictor of personal expo-  
 547 sure; rather, the most exposing source is the primary  
 548 contributor to exposure.

549 The question now is how actionable this informa-  
 550 tion is with respect to exposure reduction. To an-  
 551 swer, we focus on the Wi-Fi-connected sources and

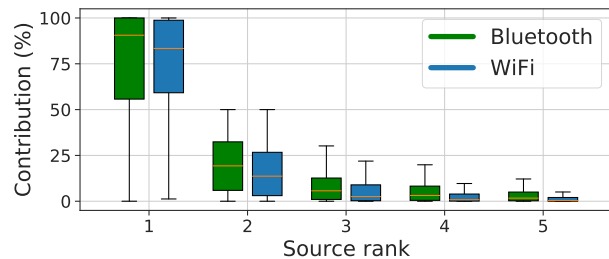


Figure 3: **The most exposing source is the primary driver of individual exposure.** This figure represents the distribution of the percentage contribution of the top five exposure sources in all exposure scans, with Bluetooth in green and Wi-Fi in blue (the boxplot convention is the following: the middle 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). 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. We observe that for 75% of the exposure scans (containing at least one Bluetooth measurement), the most exposing Bluetooth source represents at least 56% of the entire Bluetooth exposure.

552 Bluetooth-bounded devices to which a user has al-  
 553 ready connected. Connected sources or bounded de-  
 554 vices are usually owned or controlled by the user and  
 555 can therefore be switched off or moved to reduce expo-  
 556 sure. Taking all scans into account, we computed  
 557 that 41% of the time, the most exposing of all the  
 558 Wi-Fi sources is a connected one. For Bluetooth,  
 559 the most exposing source is a bounded device 10%  
 560 of the time. Then, we computed what the individual  
 561 personal exposure would have been if all connected  
 562 sources and bounded devices had been switched off.  
 563 While this is an overly optimistic situation, the goal  
 564 is to assess the degree to which an individual could  
 565 control exposure. Figure 4 shows that, by switching  
 566 off the connected sources and bounded devices, half  
 567 of the users could have reduced their total exposure  
 568 by 50% (a reduction by 3.1 dB), and 25% could have  
 569 reduced their total exposure by 90% (a reduction by  
 570 10 dB).

571 *In summary, the growth of total exposure is not*  
 572 *explained by a multiplication of sources. On the con-*  
 573 *trary, a handful of sources generate most of the per-*  
 574 *sonal exposure at any given time, and it is not uncom-*

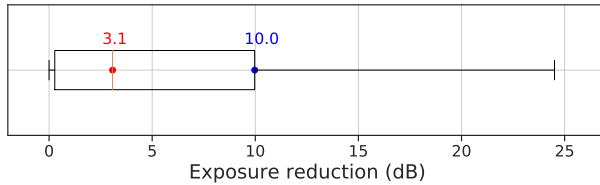


Figure 4: **By switching off connected Wi-Fi sources and bounded Bluetooth devices, 50% of the users can reduce their exposure by 3.1 dB, and 25% of the users can reduce it by at least 10 dB.** This figure shows the distribution of the individual exposure reduction for each user when we remove connected Wi-Fi sources and bounded Bluetooth devices. In red, we show the median and in blue, the 75<sup>th</sup> percentile. For each user and month, we first compute the per-user monthly average exposure. Then, for each user and month, we collect all connected Wi-Fi sources and bounded Bluetooth devices, and we 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. The result is the distribution shown in this figure for each user. 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.

575 *mon that an individual’s exposure is almost entirely*  
 576 *the result of sources they either own or associate with*  
 577 *(for a quarter of our subjects, such sources account*  
 578 *for 90% of exposure).*

### 579 3.3. Impact of regulation on personal exposure

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

#### 591 3.3.1. Cellular regulation

592 The maximum allowed exposure of the population  
 593 is fixed by the ICNIRP international body [37]. How-  
 594 ever, each country is free to lower the maximum expo-  
 595 sure depending on local policies. In addition, some  
 596 countries have policies specific to some areas (e.g.,  
 597 Belgium has different limits for Flanders, Wallonia,  
 598 and Brussels) or specific to some contexts (e.g., Italy  
 599 enforces lower exposure near schools). Finally, the  
 600 limits are specific to the frequencies used by cellular  
 601 technologies. Here, we specifically focus on the fre-  
 602 quencies 900 MHz, 1800 MHz, and 2100 MHz. For  
 603 each country, we build a regulation limit triplet, one  
 604 limit per frequency.

605 To the best of our knowledge, there is no cen-  
 606 tral repository of exposure limits for all countries.  
 607 To obtain a regulation limit triplet for each of the  
 608 13 countries we consider, we consolidated several  
 609 sources [38, 39, 26], and when multiple limits were  
 610 provided (due to local policies or context), we keep  
 611 the limit covering the largest population.

612 Figure 5 does not show any clear correlation be-  
 613 tween regulation limits and exposure. We must be  
 614 careful interpreting this result as there are several  
 615 external factors that we do not control, such as the  
 616 deployment strategy of the cellular operators. For  
 617 example, operators might decide, in a densely pop-  
 618 ulated area, to have a higher density of base sta-  
 619 tions (to increase the supported load) emitting at a  
 620 lower power (to reduce interference). In such cases,  
 621 base stations expose the population at a level that  
 622 is significantly lower than what the regulation per-  
 623 mits [26, 15]. Therefore, in practice, the regulation is  
 624 an upper bound to the population exposure in some  
 625 extreme cases, but in most cases, the population is  
 626 exposed at levels much lower than the regulation lim-  
 627 its.

628 To confirm this hypothesis, we computed the dis-  
 629 tribution of the cellular measurements in V/m. We  
 630 obtain the electric field  $E$  in V/m from the measured  
 631 received power in dBm with the formula:

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

632 where  $G$  is the antenna gain,  $f$  is the frequency in Hz,

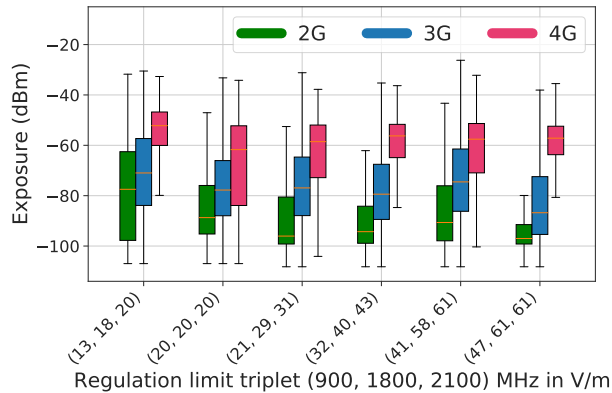


Figure 5: **We observe no correlation between regulation limits and exposure.** This figure shows the correlation between the exposure and a regulation limit triplet for the three cellular technologies we measure, 2G, 3G, and 4G (the boxplot convention is the following: the middle orange line shows the 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). 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.

633  $P$  is the power in dBm, and  $c$  is the speed of light [40].  
 634 The antenna gain of the smartphone is unknown, so  
 635 we assume an isotropic antenna (i.e.,  $G = 1$ ). In our  
 636 dataset, we have access to the cellular frequency  $f$  for  
 637 serving cells only. Therefore, we only keep exposure  
 638 scans with a serving cell containing a valid frequency  
 639 (they represent 74.5% of all exposure scans). We sum  
 640 all the cellular RSSI<sup>2</sup> in each exposure scan and convert  
 641 the summed RSSI into V/m using the frequency  
 642 of the serving cell.

643 Figure 6 shows the distribution of the measured  
 644 electric field for each exposure scan per country. We  
 645 see that the current population exposure is orders of  
 646 magnitude lower than any current regulation limit.  
 647 We found that by considering all countries together,

<sup>2</sup>As explained in Materials and Methods, 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.

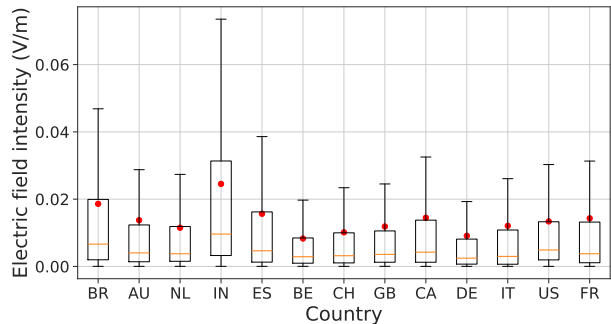


Figure 6: **The population exposure is orders of magnitude lower than any existing regulation limits for the considered countries.** This figure shows the distribution of the estimated electric field produced by cellular antennas at the receiver per country using boxplots, where the middle orange line 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. The red dot shows the mean. Considering all signals together, we have a median at 0.005 V/m, and a 99<sup>th</sup> percentile at 0.18 V/m.

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, as described in Materials and Methods, the maximum cellular RSSI that we can measure is  $-51$  dBm, so measurements above  $-51$  dBm are capped. However, measurements at  $-51$  dBm represent only 1.8% of all measurements, a very small fraction that cannot fundamentally change our conclusions. Second, we apply 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 Equation 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.*[41], 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 Equation 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

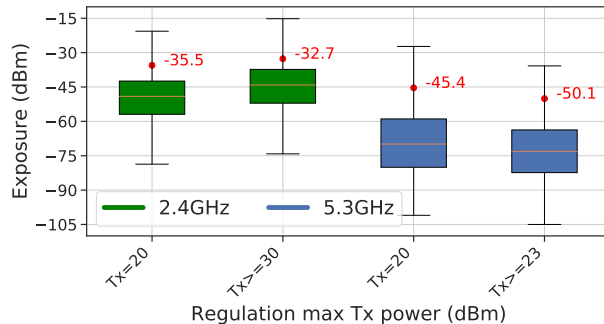


Figure 7: **The mean exposure is significantly higher when the Tx power is higher in the 2.4 GHz band, but significantly lower in the 5.3 GHz band.** The figure shows the distribution of the per-user monthly average exposure using boxplots. The middle orange line shows the median, the lower and higher 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. The red dot shows the mean. To compute the significance of the mean, we perform 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.

672 sources of error, the actual exposure in V/m could  
 673 be 4.4 times higher than what we report in Figure 6,  
 674 which is still orders of magnitude lower than the most  
 675 restrictive regulation limits in the countries we consider.  
 676

677 *In summary, 99% of our exposure scans report a*  
 678 *cellular exposure lower than 0.18 V/m (corrected to*  
 679 *0.79 V/m if we take into account the multiplying factor*  
 680 *of 4.4, corresponding to a worst-case estimate scenario),*  
 681 *which is orders of magnitude lower than any*  
 682 *regulation limits in the considered countries.*

### 683 3.3.2. WiFi regulation

684 Wi-Fi is a generic term that gathers together a  
 685 large number of standards covering a wide spectrum  
 686 of frequencies in the 2.4 GHz and 5 GHz bands. For  
 687 Wi-Fi, the goal of regulation is to reduce interference  
 688 by limiting the maximum transmission power. This  
 689 limit might be different for each country and each  
 690 frequency. Getting a consolidated view of the various  
 691 international regulations on Wi-Fi is tricky. For  
 692 this purpose, we rely on the efforts of J. W. Linville  
 693 and S. Forshee, who maintain a consolidated file con-

694 taining the Wi-Fi emitting power per country and  
 695 frequency for the Linux kernel [42].

696 To understand the impact of regulation on exposure,  
 697 we focus on two frequency bands that include a large  
 698 enough number of countries using different regulations:  
 699 2.4 GHz ([2400, 2483] MHz) and 5.3 GHz ([5250,  
 700 5350] MHz). The 2.4 GHz (resp. 5.3 GHz) band  
 701 represents 76% (resp. 2%, still 37 million measurements)  
 702 of all Wi-Fi measurements. In the 2.4 GHz band,  
 703 the maximum transmission power is 36 dBm for  
 704 Australia, 30 dBm for the USA and Canada, and  
 705 20 dBm for all the other considered countries. In  
 706 the 5.3 GHz band, the maximum transmission power  
 707 is 24 dBm for Brazil, India, and Canada, 23 dBm  
 708 for the USA, and 20 dBm for all the other  
 709 considered countries.

710 Figure 7 shows that in the 2.4 GHz band, a Tx  
 711 power of 20 dBm leads to significantly lower exposure  
 712 than a Tx power higher than 30 dBm. Therefore,  
 713 this regulation clearly impacts population exposure.  
 714 Surprisingly, when we observe the exposure for the  
 715 5.3 GHz band, we have the opposite result: a Tx  
 716 power of 20 dBm leads to significantly higher  
 717 exposure than a Tx power over 23 dBm.

718 We can explain this seemingly contradictory result.  
 719 Unlike regulations for cellular, regulations for Wi-Fi  
 720 limit the Tx power; therefore, it is not surprising  
 721 to see that Tx power impacts population exposure.  
 722 When the difference in Tx power is large (a minimum  
 723 of 10 dB between the two groups in the 2.4 GHz  
 724 band), the Tx power dominates the other factors  
 725 that affect population exposure. However, when the  
 726 difference in the Tx power is small (a maximum of  
 727 4 dB for the 5.3 GHz band), other factors dominate  
 728 the population's exposure. Indeed, as the attenuation  
 729 increases with the frequency (see Equation 1), a  
 730 small 4 dB difference in the Tx power will have a  
 731 marginal impact on the total exposure compared to,  
 732 for instance, the deployment and density of Wi-Fi  
 733 access points per country.

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

739 *3.4. The population is most exposed at home*

740 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<sup>3</sup> 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.

741 To cluster measurements according to the user location, we need users with a large enough number of measurements to identify the home location; we call them *dense users*. More precisely, when we compute the per-user monthly average exposure, we only keep users with at least 14 days of data in that month and at least 80% hourly sampling 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.

742 Finally, we use the DBSCAN algorithm [45] ( $\epsilon = 100$  meters,  $\text{minPts} = 24$ ,  $\text{distance} = \text{haversine}$ ) 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, including those frequented for work, transportation, etc.

743 Figure 8 shows that users at home are significantly less exposed to cellular radiation. The main reason is that cellular antennas are outside, so walls attenuate the radiation. Conversely, exposure to Wi-Fi is more important at home than out-of-home. Here, the increased adoption of Wi-Fi technology at home

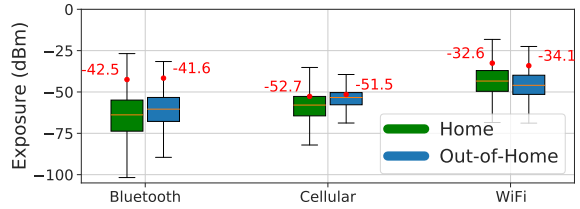


Figure 8: **The mean exposure is significantly lower at home for cellular (-1.19 dB) and higher at home for Wi-Fi (+1.55 dB).** This figure shows the distribution of the per-user monthly average exposure for dense users when they are at home (in green) and out-of-home (in blue) for Bluetooth, Cellular, and Wi-Fi sources. In the boxplots, the middle orange 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. 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.

744 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.

745 *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.*

793 **4. Discussion**

794 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

<sup>3</sup>According to the US Census Bureau, 81% of USA households had internet access in 2016 [43]. 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) [44].

800 evolution of radio frequency exposure at population-  
801 scale for 13 countries over four years. This change of  
802 paradigm from previous small-scale studies has direct  
803 consequences for the current debate on population  
804 exposure and the impact of this exposure on health.

805 The Council of Europe, following the principle of  
806 precaution, has called for an *As Low As Reasonably*  
807 *Achievable* (ALARA) rule [46]. In line with this prin-  
808 ciple, one proposal is to reduce exposure levels as  
809 low as 0.6 V/m and even 0.2 V/m in the medium  
810 term. The debate currently includes proponents, who  
811 see ALARA as a necessary drastic reduction to curb  
812 the current level of exposure, and cellular operators,  
813 who oppose ALARA by arguing that it would impede  
814 the deployment of communication infrastructure, and  
815 thus, eventually, access. We reveal that for the vast  
816 majority of the population, exposure is already be-  
817 low the lowest ALARA level. However, reducing the  
818 current regulation levels would still benefit the small  
819 fraction of the population that is currently more ex-  
820 posed than recommended by the ALARA rule.

821 Our work also fundamentally changes the debate  
822 on frequency exposure, currently heavily centered on  
823 the regulation of cellular operators. Not only do we  
824 show that Wi-Fi is by far the largest contributor  
825 to population exposure, but also that a few sets of  
826 sources, namely those used by individuals and those  
827 present at home, are the key contributors. Offering  
828 tools for individuals to prevent unnecessary exposure  
829 at home, or working on technology that automatically  
830 reduces exposure are just some examples of short and  
831 medium term ways to expand the precautionary prin-  
832 ciple. Such approaches have not yet received the at-  
833 tention that they deserve.

834 Beyond these direct implications, we envision our  
835 work and dataset providing a foundation for future  
836 epidemiological studies.

### 837 CRediT authorship contribution statement

838 **Y. Boussad:** Conceptualization, Data curation,  
839 Formal Analysis, Investigation, Methodology, Soft-  
840 ware, Validation, Visualization, Writing original  
841 draft, Writing review & editing. **X. Chen:** For-  
842 mal Analysis, Methodology, Software, Validation,

Visualization, Writing original draft, Writing re-  
view & editing. **A. Legout:** Conceptualization,  
Data curation, Formal Analysis, Funding acquisi-  
tion, Investigation, Methodology, Project adminis-  
tration, Resources, Software, Supervision, Valid-  
ation, Writing original draft, Writing review & editing.  
**A. Chaintreau:** Conceptualization, Formal Analy-  
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The authors declare no conflict of interest.

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