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STUDY PROTOCOL

REVISED Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study to derive conversion functions

[version 2; peer review: 3 approved, 1 approved with reservations]

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Abstract

Mobile phones continuously monitor and evaluate indicators of the received signal strengths from surrounding base stations to optimise wireless services. These signal strength indicators (SSIs) offer the potential for assessing radiofrequency electromagnetic field (RF-EMF) exposure on a population scale, as they can be related to exposure from both base stations and handset devices. Within the ETAIN (Exposure To electromAgnetic fields and plaNetary health) project, an open-access RF-EMF exposure app for smartphones, named "ETAIN 5G-Scientist", has been developed using citizen science. This paper delineates a measurement protocol for deriving formulas to convert the app SSIs into electric field values to estimate RF-EMF exposure. It presents pilot study results from measurements taken at four locations in France (FR), and 14 locations in the Netherlands (NL), using three different phone models and the most common network providers in each country. The measurements were conducted while executing different usage scenarios, such as calls or data transmission. The exposimeter ExpoM-RF4 and on-body electric field

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probes were used to measure exposure from far-field sources and the handset, respectively. Two-minute aggregates were considered the sample unit for analyses (n=891 in NL, n=395 in FR). Regression analyses showed a positive log-linear relationship between Long Term Evolution (LTE) Received Signal Strength Indicator (RSSI) and far-field RF-EMF exposure when aggregating data by location (coefficients for normalised RSSI: 0.91 [95% CI: 0.55 - 1.28] in FR, 1.09 [95% CI: 0.96 - 1.22] in NL). Negative log-linear trends were observed for handset-related RF-EMF exposure at the ear (-0.31 [95% CI: -0.46 - -0.16]) and chest (-0.20 [95% CI: -0.37 - -0.03]) during data transmission scenarios. These results demonstrate that the ETAIN 5G-Scientist app can be implemented for smartphone-based RF-EMF estimation. However, uncertainties in individual measurement points highlight the need for further data collection and analysis to improve the accuracy of exposure estimates.

Plain Language Summary

In this study, we looked at how mobile phones can help us measure exposure to radiofrequency electromagnetic fields (RF-EMF) from mobile wireless communication. As part of the ETAIN project (Exposure To electromAgnetic fields and plaNetary health), we developed an app called "5G Scientist" to keep track of the signal strength indicators (SSIs) that smartphones continuously use to establish and improve wireless connections. Our goal is to study how these indicators are related to RF-EMF exposure and to develop formulas for converting them into exposure values. To achieve this, we developed a measurement protocol and tested it in a pilot study. In this pilot study, we took spot measurements in France and the Netherlands using various phone models and network providers, while applying different usages of the phone, e.g. voice or video calls and data transmission. We used a personal exposimeter to measure exposure from far-field sources (such as base stations) and on-body electric field probes to measure exposure from near-field sources (such as own phone use). Our measurements indicate that as signal quality improves, exposure from mobile phone base stations increases, whereas exposure from one's own device decreases in both strength and duration. These results suggest that smartphone apps could serve as valuable tools for large-scale exposure assessment, as they show the potential to capture ambient exposure as well as exposure coming from the own mobile phone. However, more extensive measurement campaigns are needed to make this method more accurate.

Keywords

Radiofrequency electromagnetic field (RF-EMF) exposure, smartphone app, signal strength indicators, measurement protocol, spot measurements, conversion functions

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REVISED **Amendments from Version 1**

The revised manuscript includes several updates to enhance clarity, methodological transparency, and data interpretation. The app's name was corrected to its final published version, ETAIN 5G Scientist app. The introduction was expanded to better explain the observed negative correlation between signal strength indicators and transmitted power and to clarify the novelty of the app compared to similar applications, particularly its citizen science approach and the methodology for RF-EMF exposure estimation based on smartphone collected data. A recent reference discussing the relationship between signal strength indicators and exposure measurements was also incorporated. Corrections were made to figures and tables to address typos and improve the clarity of data visualization. The data aggregation process was further detailed, with additional explanations on how multiple signals were combined, the rationale for the two-minute averaging window, and the synchronization of mobile and exposimeter data. The discussion of model sources of uncertainty has been included, along with their effects on regression analysis and the limitations of each conversion function. Finally, the study's scope has been clarified, acknowledging that the current conversion functions are limited to 4G-LTE technology due to the limited deployment of 5G-NR in Europe at the time of data collection.

Any further responses from the reviewers can be found at the end of the article

Introduction

To meet the ever-growing demand for enhanced connectivity in our modern era, wireless telecommunication technologies have consistently and rapidly evolved over the past few decades. The transition from the analogue networks of the first generation (1G) to the ultra-fast data speeds promised by the fifth-generation New Radio (5G-NR), has involved the introduction of new frequency bands and transmission techniques[1]. The pervasive deployment of wireless communication infrastructures is accompanied by the escalating complexity and diversity of networks. As a result, exposure patterns may change, presenting new challenges in evaluating exposure to radiofrequency electromagnetic fields (RF-EMFs). Accurate exposure assessment is crucial for understanding and mitigating any public and scientific concerns regarding potential health effects associated with RF-EMF from wireless technologies.

Depending on the emitting source, two components of RF-EMF exposure can be distinguished. One is the uplink (UL) exposure, which is produced by the signals transmitted from the handset to the radio base station antennas. The other is the downlink (DL) exposure, which is composed of signals emitted by the base station antennas to user devices. Typically, UL exposure is self-induced, more localized, and originates from near-field sources situated within the Fraunhofer limit of the human body's position[2]. In contrast, DL exposure has been considered environmental far-field exposure due to its association with fixed installations[3]. With the advent of advanced technologies in 4G-LTE and 5G-NR base stations, such as beam-steering or Massive Multiple-Input Multiple-Output (MaMIMO), DL exposure dynamics have evolved[4]. MaMIMO technology adjusts the phase and amplitude of the DL emissions to optimize the signal-to-noise ratio at the location of the receiving device, resulting in EMF beamforming[5]. Consequently, DL exposure includes now a self-induced component that could result in increased RF-EMF exposure of users[4,6].

Conventional RF-EMF exposure assessment approaches, reliant on fixed antenna patterns, face potential obsolescence with the adoption of adaptive antenna array systems. Additionally, the considerable spatiotemporal variability of RF-EMF continues to present challenges for accurate exposure assessment. The instruments used to record exposure quantities, comprehensively reviewed by Bhatt *et al.*[7,8] are often expensive and can be bulky or heavy, making them cumbersome to carry. This limits measurements over extended periods of time or across large geographic areas and with large population samples. To circumvent these limitations, the use of smartphones as instruments to measure personal RF-EMF exposure has been proposed[9–11].

Mobile phones are usually equipped with a multi-band antenna and routinely monitor the signal strengths of surrounding cells. Certain indicators of these signal strengths are calculated as means of quantification. These indicators are used in several network-related functions such as network discovery, connection establishment, and connection maintenance. Due to their role in connecting smartphones to the base stations and quantifying the received power at the connected antenna, signal strength indicators (SSIs) are potentially directly correlated with the DL component of the underlying electromagnetic field strength of the mobile radio network and, consequently, with ambient RF-EMF exposure[12]. The Android operating system provides access to SSIs through its application programming interface (API) functions. However, information regarding the transmitted (UL) power of mobile phones during normal use is not readily accessible and can only be obtained from the network provider or by expanding the existing hardware of the phone. Understanding transmitted power is crucial for assessing the contribution of the UL to exposure[12]. Despite this, SSIs indirectly impact the power transmitted by the handset by influencing its power control mechanisms[13]. Several studies have reported a robust negative correlation between SSIs and transmitted power[12,14,15], due to path loss compensation and signal-to-noise ratio optimisation. When SSI is high, the phone is more likely to be closer to the base station, experiencing lower path loss and requiring less transmitted power to maintain a stable connection. Additionally, a stronger received signal improves the signal-to-noise ratio, allowing for more efficient communication. This negative correlation potentially allows for the utilisation of SSIs in estimating transmitted power, providing a framework for assessing both DL and UL RF-EMF exposure levels. Given the nearly universal use of smartphones, measurement data obtained through an app could, in principle, be used to estimate RF-EMF exposure on a population scale.

Currently, various smartphone applications offer the ability to collect information about SSIs from mobile and Wi-Fi

networks. Examples include XMobiSense[9], ElectroSmart[10], Quanta Monitor[16,17], and QualiPoc Android[18]. Some of these apps have incorporated algorithms to estimate RF-EMF exposure based on the collected SSIs. ElectroSmart, for instance, provides an exposure index derived from Wi-Fi and mobile technologies. Quanta Monitor measures RF-EMF exposure (in $\mu W\ m^{-2}$) and offers real-time estimates of the specific absorption rate (SAR, in $W\ kg^{-1}$). However, there is limited scientific literature describing the methods and providing data used by these apps for converting app-generated data into power density, SAR or field strength values. Further, these relations may change over time in parallel with technological changes such as the introduction of 5G. Hence, it is difficult to rely on these apps for scientific studies.

Fröhlich *et al.*[19] and Schießl *et al.*[20] conducted feasibility studies to assess whether smartphones could be used to measure RF-EMF exposure. While they concluded that a fully comprehensive monitoring system is not feasible, they underscore that smartphone-based measurements can still provide valuable and reasonably reliable information. Similarly, Lopez-Espi *et al.*[21] proposed a methodology for exposure mapping using app-collected data and identified a proportional relationship between EMF measurements and SSIs. However, their approach lacked a conversion factor required to estimate exposure levels from smartphone data.

This study aims to investigate the relationship between SSIs and RF-EMF exposure related to mobile phone use, providing a reproducible framework for estimating RF-EMF exposure using an open-access smartphone app suitable for scientific studies. In this paper, we present the measurement procedures necessary for the derivation of conversion functions to estimate RF-EMF exposure from far-field sources and from the handset using cellular SSIs, along with results from a pilot study conducted to test the feasibility of the measurement protocol.

Objectives

This work is part of the European Union's Horizon-funded ETAIN (Exposure To electromAgnetic fIelds and plaNetary health) project. ETAIN takes a planetary health perspective to develop and validate approaches to assess the impact of existing and novel wireless technologies while exploring options for exposure reduction. Within this framework, we developed an open-access RF-EMF exposure app for smartphones, named "5G Scientist", using a citizen science approach. To align with public expectations and needs, a co-design process involving citizens and experts determined the app's functionalities, interfaces, and relevant exposure indicators. The app is currently in the launch phase, and is already available on the Play Store[22]. Data collected by European citizens will be used as input information to calculate spatially resolved exposure maps. These maps will offer insights into population exposure to RF-EMF from mobile telecommunication technologies.

This paper presents a measurement protocol that fulfils the following three key requirements[19]: (1) recording RF-EMF exposure from all mobile network providers and various mobile radio technologies; (2) testing various common smartphone models; and (3) considering different positions of the smartphone in relation to users' bodies. In adherence to these requirements, the protocol was pre-tested in Lyon (FR) at four locations. Subsequently, it was applied as a pilot study in 14 locations in the Netherlands. The aim of the pre-test and pilot studies was to streamline the protocol for full implementation in two European countries, the Netherlands (NL) and Switzerland (CH), while also identifying key features for applying a shortened version in three other European countries: Germany (DE), Greece (GR), and Spain (ES).

Methods

Spot Measurement Protocol

Measurement Locations and Study Areas. Measurements are taken at different locations per country within two urban and two rural areas. Urban and rural areas are defined based on the level of urbanisation given by the harmonized definition of cities and rural areas of the European Commission[23]. The number of locations per area comprises a minimum of five locations in urban areas and two locations in rural areas. The locations are selected based on the type of microenvironment, network density, and accessibility or ease of measurement. Initially, potential locations are identified according to microenvironment types as defined by the Corine Land Cover (CLC) nomenclature guidelines[24]. This protocol focuses on four CLC classes considered relevant microenvironment types: city centre and residential areas (CLC codes: 111, 1121-1124), industrial and commercial areas (CLC code: 121), transportation network (1221-1223), and green areas (CLC codes: 141-142). To identify each type of microenvironment within each urban or rural area, the Urban Atlas 2018[25] is used and vector layers for each area are displayed using GIS software[26]. For urban areas, the allocation of locations per microenvironment is as follows: two locations in the city centre and residential areas (one indoor and one outdoor), one in industrial and commercial areas (indoor), one in transportation networks (indoor, usually the main train station), and one in a green urban area (outdoor). In rural areas, the distribution is one location in the town centre and residential areas (outdoor) and one in the transportation network (outdoor, usually local transport stations).

The final selection criteria to choose locations is based on the 4G-LTE and 5G-NR network density. National data on antenna locations is used for this purpose. In the context of this protocol, network density at a location is defined as the total number of deployed antennas within a one-kilometre circular area surrounding a location, encompassing coverage in the LTE-Advanced and 5G-NR era[27]. Using GIS software[26], the network density is determined alongside the microenvironment type. Network density is used as a guide to select locations that represent different network load scenarios within each urban and rural area. Additionally, network density is used to select locations with comparable network loads across countries.

Measurement Setup. At selected locations, measurements are carried out using a smartphone, on which the ETAIN 5G Scientist app is installed, a personal exposimeter (ExpoM-RF4[28]) to assess far-field exposure, and two custom-built electric field on-body probes[29] to evaluate exposure from the handset (Figure 1). A trained researcher conducts simultaneous measurements with all tools while executing different

usage scenarios with the phone (described below). The ExpoM-RF4 is mounted on a non-metallic tripod positioned in front of the researcher at a height of 115 cm and a minimum distance of 30 cm from the smartphone. The two on-body electric field probes are placed on top of the researcher's skin or clothes: one positioned in front of the tragus of the right ear and the other along the midline of the chest. The 5G Scientist app recordings are repeated using three different smartphone models supporting 5G-NR technology. To ensure access to representative data, the app measurements are also repeated using SIM cards from the most prevalent mobile network providers in each respective country (Table S1 in Extended Data[30]).

Measurement Tools. The ETAIN 5G Scientist app uses data accessible through standard API functions and is currently implemented in the Android platform. It records data from the underlying operating system, providing information on cellular technologies and connected Wi-Fi and Bluetooth networks (Tables S2–S4, in Extended Data[30]). The app logs the timestamp for each recording with local time in Coordinated Universal Time (UTC), with cellular data recorded every second and Wi-Fi/Bluetooth information recorded every ten seconds. Cellular information monitored by the app includes the most important SSIs for different technologies (Table 1)[31], as well as frequency and/or channel information

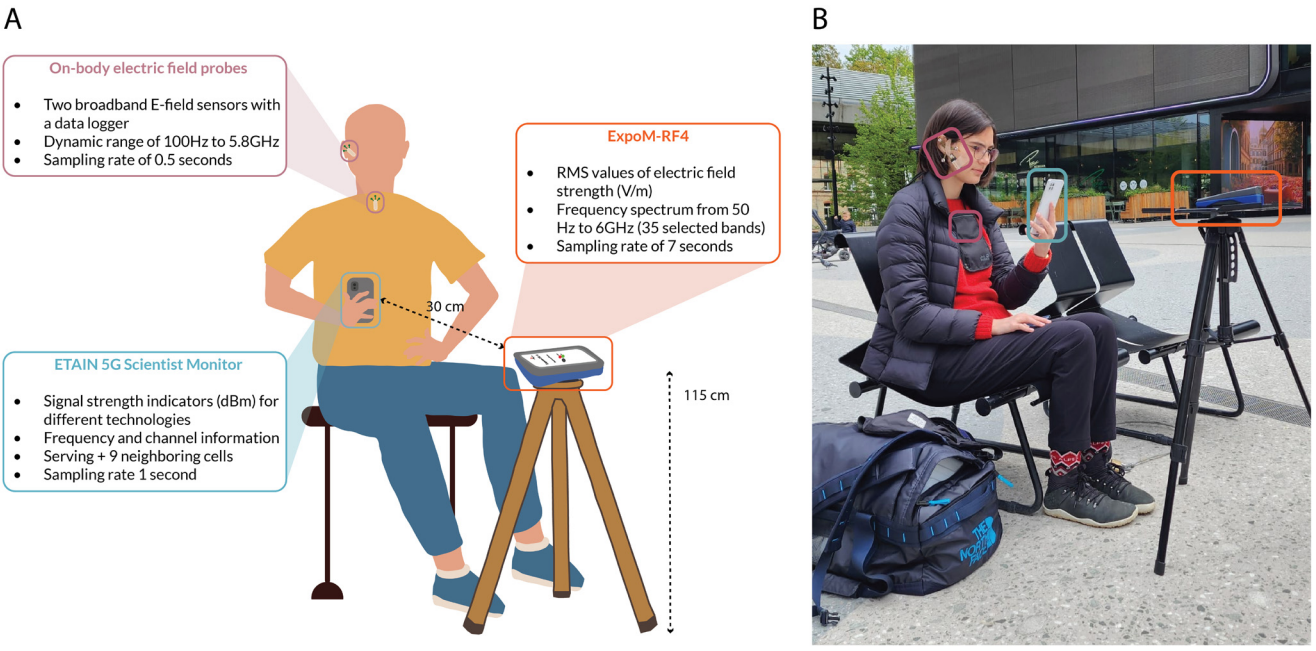

Figure 1. Illustration (**A**) and real-life (**B**) representation of spot measurement setup.

Table 1. Overview of key Signal Strength Indicators* (SSIs) recorded with the ETAIN 5G Scientist app and their value ranges.

Technology	SSI	Description	Range [dBm]
3G-WCDMA	RSCP	Received power measured on one code of the pilot bits (reference signal) of a radio cell (usually the Primary Common Pilot Channel).	-120 to -25
4G-LTE	RSSI	Linear average of the total received power within the measurement bandwidth, including other power contributions besides the reference signal, such as neighbouring radio cells, interference, and thermal noise.	-113 to -51
	RSRP	Linear average of the power contributions of the resource elements that carry the cell-specific reference signal.	-156 to -44
5G-NR	SS-RSRP	Linear average of the power contributions of the resource elements that carry the secondary synchronization signal.	-156 to -31

*As defined by the 3rd Generation Partnership Project (3GPP)[31]

SSI=Signal Strength Indicator; WCDMA= Wideband Code Division Multiple Access; LTE=Long Term Evolution; NR=New Radio; RSCP= Received Signal Code Power; RSSI= Received Signal Strength Indicator; RSRP=Reference Signal Received Power; SS-RSRP= Synchronization Signal Reference Signal Received Power.

from the serving and up to nine neighbouring radio cells. SSIs are reported in dBm (decibel milliwatts: absolute power on a logarithmic scale), with varying ranges depending on the mobile communication standard. The serving cell, identified as index 0 in the app's recordings, refers to the specific cell within the network currently providing telecommunication services to the mobile phone. Neighbouring cells, indexed from 1 to 9 in the app's recordings, are adjacent to the serving cell and are part of the same network infrastructure of the subscribed provider. Additionally, the app tracks the total number of received and transmitted bytes over all networks. All information collected with the app is stored in the internal memory of the phone and can be downloaded as a CSV file.

The ExpoM-RF4, a portable frequency-selective personal exposimeter developed by Fields at Work GmbH[28], measures the Root Mean Square (RMS) and peak values of electric field strength (in V m^{-1}) across a frequency spectrum from 50 MHz to 6 GHz. We have established 35 frequency bands for measurement, encompassing the main frequencies used in mobile telecommunication technologies across Europe[32] (Table S5 in Extended Data[30]). Sampling occurs continuously and is configured at an interval of seven seconds, during which every frequency band is measured for a duration of 50 ms. The upper limit of detection is 6 Vm^{-1} for all frequency bands, while the lower limit varies from 0.0009 to 0.01 V m^{-1} depending on the band.

The on-body field probes are novel wearable probe modules developed by Fields at Work GmbH with the aim of directly measuring RF-EMF near-field exposure on the body[29]. Each probe consists of a flexible circuit board with three integrated broadband E-field sensors (channels A, B, and C) and a data logger (Figure S1 in Extended Data[30]). These sensors use diode detectors to measure any EMF within a dynamic range of 100 to 5800 MHz at a sampling rate of two measurements per second. They feature a lower limit of detection of approximately 2 Vm^{-1} and a saturation upper limit of up to 267 Vm^{-1} (Table S6 in Extended Data[30]). Each sensor produces a voltage signal proportional to the average electric field strength exposure, which is subsequently amplified, digitized, and stored in the data logger. The recorded voltage is then converted to field strength values based on a sensor-specific calibration[29].

Usage Scenarios. The measurements entail performing various scenarios with the phone, involving specific activities, telecommunication technologies, and positioning the handset relative to the body in a predetermined way. To ensure consistent measurements, we have identified 11 standardized usage scenarios (Table 2). Each scenario involves one of six

Table 2. Description of usage scenarios for spot measurements.

Scenario	Activity for 2 minutes	Technology*	Phone position
Non-use**	The phone is set in flight mode.	-	Held in the right hand in front of the body (~30 cm)
BT-music	Song playback using wireless earphones connected to the phone via Bluetooth.	Bluetooth	Held in the right hand in front of the body (~30 cm)
WiFi-WAvoice	Bidirectional reception and transmission of audio signals using WhatsApp.	Wi-Fi	Held in the right hand and pressed against the right ear
WiFi-WAvideo	Bidirectional reception and transmission of audio and video signals using WhatsApp.	Wi-Fi	Held in the right hand in front of the body (~30 cm)
WiFi-fileUpload	Continuous file upload to an FTP server.	Wi-Fi	Held in the right hand in front of the body (~30 cm)
4G-nativeCall**	Bidirectional reception and transmission of audio signals through the native service of the phone.	up to 4G-LTE	Held in the right hand and pressed against the right ear
4G-WAvoice**	Bidirectional reception and transmission of audio signals using WhatsApp.	up to 4G-LTE	Held in the right hand and pressed against the right ear
4G-WAvideo**	Bidirectional reception and transmission of audio and video signals using WhatsApp.	up to 4G-LTE	Held in the right hand in front of the body (~30 cm)
4G-fileUpload**	Continuous file upload to an FTP server.	up to 4G-LTE	Held in the right hand in front of the body (~30 cm)
5G-WAvideo**	Bidirectional reception and transmission of audio and video signals using WhatsApp.	up to 5G-NR	Held in the right hand in front of the body (~30 cm)
5G-fileUpload**	Continuous file upload to an FTP server.	up to 5G-NR	Held in the right hand in front of the body (~30 cm)

*Technology constrained within Android settings.

**Usage scenarios conducted in the pre-test and pilot studies.

BT=Bluetooth; WAvoice=WhatsApp voice call; WAvideo=WhatsApp video call; LTE=Long Term Evolution; NR=New Radio.

activities with a forced telecommunication technology. The activities include enabling flight mode, making a voice call using the phone's native services (i.e. without using any downloaded application), placing a voice call via a standard app such as WhatsApp, making a video call via WhatsApp, and continuously uploading a file to a File Transfer Protocol (FTP) server. Each activity is performed for two minutes. The phone's position relative to the body during the scenario is fixed for each activity, mimicking real-life situations. The operational technology of the smartphone is constrained within Android settings up to a certain technology (e.g. up to 4G or up to 5G) for the specific scenario. However, the actual technology used depends not only on the phone's settings but also on factors like network congestion, signal strength, and tower proximity. Thus, other legacy technologies may still be used throughout the scenario depending on these factors.

The implementation of the usage scenarios during measurements is facilitated through a bespoke mobile application called "ETAIN-scenarios", which minimises the variability attributable to trained researchers and maximises protocol standardisation. Depending on the specific usage scenario, this app serves both as an instructional manual and, in some cases, enables certain actions during the measurements (Table S7 in Extended Data[30]). Additionally, the ETAIN-scenarios app ensures that each scenario lasts two minutes, integrates error mitigation strategies and generates measurement timestamps that allow for temporal synchronisation between the recordings of all the measuring tools.

Pre-test and pilot studies

Spot measurements were carried out in Lyon, France (FR), for a pre-test of the protocol, and in the Netherlands (NL) for a pilot study. In Lyon, four locations were chosen to represent various network load scenarios across the city. In the Netherlands, 14 locations were selected, encompassing two urban (Amsterdam and Utrecht) and two rural areas (Werkhoven and Zegveld) (Table S8 in Extended Data[30]). The pilot study specifically focused on cellular technologies; thus, this paper details the measurements conducted for non-use, 4G, and 5G scenarios (Table 2).

The measurement campaigns took place in FR from July 24 to 28, 2023, and in NL from October 3 to November 21, 2023. During these campaigns, data was collected using three different smartphone models and the most common network providers in each country. In Lyon, the phone models used were Samsung S22+, Xiaomi Redmi Note 11S, and Oppo A77, while the network providers included Orange, SFR, Free Mobile, and Bouygues Telecom. In the Netherlands, the same phone models were used as in France, except for a different Samsung model (Samsung A22), and the network providers were KPN, Odido, and Vodafone. All smartphones operated on Android version 13 (API level 33).

Data analysis and modelling

Conversion functions are needed to express app SSIs as RF-EMF exposure values (i.e., electric field strength values). These functions need to consider variables that could affect the parameters recorded by the app and their correlation with DL and UL RF-EMF exposure. The general form of the conversion functions, as shown in Equation 1, relates RF-EMF exposure from far-field sources or the handset, measured with the ExpoM-RF4 and on-body electric field probes respectively, to the SSIs recorded by the ETAIN 5G Scientist app:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad (Eq.\ 1)$$

Where Y_i is the response variable for the i-th observation (RF-EMF exposure in dBµVm^{-1}), β_0 is the intercept (in dBm), β_1 is the coefficient for the predictor variable X_i, X_i denotes the normalised SSIs (in dBm) at frequency f_0, and ε_i is the error term for the i-th observation.

According to the Friis transmission equation[33], when a transmitting antenna (e.g., a base station) emits a signal with certain power, and both transmitting and receiving antennas (e.g., phone) maintain constant gains, the received power is directly proportional to the square of the wavelength. Thus, as frequency increases (resulting in shorter wavelengths), received power decreases, assuming all other variables remain constant. To compensate for this relationship between received power and frequency, SSIs are normalised to a specific frequency (f_0 = 1800 *MHz,* as a middle frequency in the spectrum used for mobile networks), when the received frequency is known (f_i), using the following formula:

$$X_i = SSI_{Measured} + 20log_{10}(f_i/f_0) \qquad (Eq.\ 2)$$

To estimate far-field exposure using SSIs, we undertook log-linear regression analyses across three levels to derive three types of far-field conversion functions, each with its own limitations and implications (see Table 3). To derive near-field conversion functions, we performed log-linear regression analyses between the exposure originating from the handset measured with the electric field probes at the ear (E_{ear}) or chest (E_{chest}) and the SSIs of the serving cell (s-SSI). Exposure from the handset is influenced not only by the transmitted power emitted by the phone but also by the exposure duration while using it. Thus, we normalised the on-body electric field probe measurements for file upload scenarios by data throughput (in megabytes per second, Mbps). In this way, s-SSI serves as a proxy of the phone's transmitted power. Given the minimal data throughput during voice call scenarios, no normalisation was conducted for these scenarios. As a validation step, we replicated the analysis using the UL exposure measured with the ExpoM-RF4.

Two-minute aggregates, corresponding to the duration of each usage scenario, were considered the sample unit for regression analyses in the technical and app conversion functions. ExpoM-RF4 measurements and 5G Scientist app recordings were temporally synchronized with each other and with the usage scenario timestamps from the ETAIN-scenarios app. Aggregates were computed for each unique combination of location, phone, provider, and scenario (n=795 in NL and n=325

Table 3. Description of the analysis levels to derive conversion functions for estimating far-field RF-EMF exposure from mobile communication technologies.

	Aim	Regression variables	Implications	Limitations
Technical conversion function	To determine the user´s DL exposure from the active band used for communication.	Response variable (Y_i): DL or TDD exposure for the receiving band ($E_{DL\text{-}ActiveBand}$); Predictor variable (X_i): SSI of the serving cell (s-SSI: sLTE-RSSI, sLTE-RSRP, or sNR-ssRSRP)	Reflects the underlying technical relationship between received power and RF-EMF exposure in the receiving band, yet it does not represent the user's total far-field exposure.	Ignores DL exposure from other base station antennas not used by the phone, including those from other providers and neighbouring cells of the same provider.
App conversion function	To determine total DL exposure using all available information from an individual ETAIN 5G Scientist app user.	Response variable (Y_i): Total DL or TDD exposure for each technology*, i.e. 4G-LTE ($E_{DL\text{-}LTE}$) or 5G-NR (E_{NR}); Predictor variable (X_i): Sum of the SSIs from serving and neighbouring cells (a-SSI: aLTE-RSSI, aLTE-RSRP, or aNR-ssRSRP)	It can be implemented in the ETAIN 5G Scientist app to provide users with a relevant exposure value and to study RF-EMF exposure on a population level.	Provides no information on DL exposure from the user's own provider.
Map conversion function	To offer information on total DL exposure aggregating by location.	Response variable (Y_i): Mean DL or TDD exposure by location for each technology*, i.e. 4G-LTE ($E_{DL\text{-}LTE}$) or 5G-NR (E_{NR}); Predictor variable (X_i): Sum of the arithmetic means of the SSIs from serving and neighbouring cells (a-SSI: aLTE-RSSI, aLTE-RSRP, and aNR-ssRSRP) for each provider at each location.	It uses the information from multiple users of the app to estimate DL exposure at a given location. Can be used for creating RF-EMF exposure maps by aggregating data across time and geographical areas from multiple users of the ETAIN 5G Scientist app.	Provides no temporal or instantaneous information on DL exposure.

*4G-LTE exposure is calculated as the sum of exposure across 700, 800, 900, 1800, 2100, and 2600 DL or TDD bands measured with the ExpoM-RF4; while 5G-NR exposure is calculated as the sum of exposure across 3500 TDD bands measured with the ExpoM-RF4.

DL=downlink; TDD=time division duplexing; LTE=Long Term Evolution; NR=New Radio; SSI=signal strength indicator; RSSI= Received Signal Strength Indicator; RSRP=Reference Signal Received Power; SS-RSRP= Synchronization Signal Reference Signal Received Power.

in FR) by taking the arithmetic mean of the app SSIs, and of the recorded ExpoM-RF4 and probe electric field strengths during the interval. Specifically, the SSIs received power values were converted in the linear scale (mW), averaged, and back-transformed to the logarithmic scale (dBm) for analyses and graphical and tabular representation. The received power of the SSIs referred to the serving cell (s-SSI) or to the sum of serving and all neighbouring cells (a-SSI) for each aggregate. In cases where the serving cell changed during the two-minute intervals for 5G and 4G scenarios, we further subdivided the aggregates based on the serving cell, resulting in a total sample size of 891 in the Netherlands and 395 in France. In both countries, we observed a maximum of three different serving cells during the two-minute aggregates, with two or more serving cells in 68 (20.9%) of the aggregates in France and 87 (10.9%) in the Netherlands.

For the map conversion function, location aggregates were used as the sample unit for regression analyses (n=14 in NL, n=4 in FR). These aggregates were calculated by averaging the app SSIs for each provider at each location, considering both the serving and neighbouring cells (a-SSIs). The averages for all available providers were then summed by location to represent the total received power. Aggregation was performed in the linear scale (mW), and the values were subsequently back-transformed to the logarithmic scale (dBm) for the analyses. Additionally, the arithmetic mean per location of the recorded ExpoM-RF4 total DL and TDD exposure for each technology was calculated (see below).

Apart from the SSIs, the 5G Scientist app provided details about the operational frequencies of both serving and neighbouring cells. The frequency was determined using the LTE Evolved Universal Terrestrial Radio Access (E-UTRA) Absolute Radio Frequency Channel Number (EARFCN), NR Absolute Radio Frequency Channel Number (NRARFCN), or UTRA Absolute Radio Frequency Channel Number (UARFCN), depending on the technology employed by the

serving cell (Table S9 in Extended Data[30]). Using the serving cell frequency information, exposure measured by the ExpoM-RF4 was assigned to the corresponding DL, UL, and TDD active band ($E_{DL-ActiveBand}$, $E_{UL-ActiveBand}$, and $E_{TDD-ActiveBand}$).

Prior to any computations involving the ExpoM-RF4 data, a cross-talk correction was applied for frequency bands less than 100 MHz apart, following the methodology described by Eeftens *et al.*[34]. The electric field strengths recorded by the ExpoM-RF4 were transformed into power flux density, measured in mWm^{-2}, to facilitate the calculation of the aggregates and determine total (E_T), downlink (E_{DL}), uplink (E_{UL}), and Time Division Duplex (E_{TDD}) exposures overall and for each technology (i.e. E_{DL-LTE}, E_{UL-LTE}, and E_{NR}). E_T was calculated as the power density sum of all 35 bands. E_{DL} was computed as the sum of the following bands: 700 DL (centre frequency: 770.5 MHz), 800 DL (808.5 MHz), 900 DL (942.5 MHz), 1400 DL (1479.5 MHz), 1800 DL (1842.5 MHz), 2100 DL (2145 MHz), and 2600 DL (2657 MHz). E_{UL} was calculated as the sum of 700 UL (718 MHz), 800 UL (847 MHz), 900 UL (897.5 MHz), 1800 UL (1747.5 MHz), 2100 UL (2535 MHz), and 2600 UL (2535 MHz) bands. E_{TDD} was determined as the sum of all TDD bands, i.e. 700 (748 MHz), 2600 (2592.5 MHz), and 3500 (3475, 3605, and 3735 MHz). By technology, E_{DL-LTE} and E_{UL-LTE} represent the sum of power densities across 700, 800, 900, 1800, 2100, and 2600 DL, UL or TDD bands; whereas E_{NR} is the sum of 3500 TDD bands. Upon completing the necessary computations, the results were converted to a logarithmic scale ($dB\mu Vm^{-1}$) for modelling purposes as we expected a log-linear relationship between electric field strengths and the received power of the SSIs.

We performed a data quality assessment of the on-body electric field probe measurements. Measurements below the detection limit (<2 Vm^{-1}) were excluded from the analysis. In the Lyon dataset, the field probes encountered an electrical issue resulting in a loss of connection between the sensor and the data logger. Consequently, the field probe data collected in Lyon was deemed invalid and was excluded from the analyses. For the Netherlands dataset, the highest recorded value among the three channels of each probe was used as the proxy for peak exposure from the handset. Similar to the approach taken with the ExpoM-RF4 data, electric field strengths recorded by the probes were converted into power flux density (mWm^{-2}) for computing the arithmetic means of peak exposure over the two-minute aggregates. Since the electric field probes are not frequency-specific, we addressed environmental exposure by using measurements obtained during non-use scenarios specific to each combination of location, phone model, and network provider. For each aggregate, the exposure recorded during the corresponding non-use scenario was subtracted from the measured exposure during active usage. This subtraction process yielded adjusted exposure aggregates intended to isolate handset-related exposure. Subsequently, the reconverted electric fields were transformed onto a logarithmic scale ($dB\mu Vm^{-1}$) for data analyses. As our focus is on exposure resulting from the phone's transmitted power emission, two-minute aggregates without successful data transmission (information provided by the 5G Scientist app) were not considered in the derivation of the near-field conversion function. From the data cleaning process described above, peak exposure at the ear occurred during voice call scenarios and file upload scenarios (n=85). Similarly, peak exposure at the chest occurred during the file upload scenarios (n=30). Regression analyses were conducted separately for scenarios where the phone was positioned against the ear (4G native and WhatsApp calls) and scenarios where the phone was in front of the body (file upload), as the distance between the phone and the electric field probe directly influenced the measured exposure.

All analyses were performed using R (version 4.3.2) within RStudio (version 2023.09.1.494). Kendall's tau was used to determine rank correlation coefficients, and linear regression was employed to establish the conversion functions.

Results

Descriptive statistics

The mean total exposure across all locations during non-use scenarios was observed to be lower in NL compared to FR, with respective values of 0.84 Vm^{-1} (Interquartile Range [IQR] =1.13 Vm^{-1}) and 1.01 Vm^{-1} (IQR=2.40 Vm^{-1}). The difference in environmental exposure between the two countries was due to higher exposure levels in broadcast or infrastructure bands in Lyon (see Table S10 in Extended Data[30]). Figure 2 shows the mean total exposure recorded by the ExpoM-RF4 per usage scenario in each country. Overall, there was virtually no difference in DL exposure between usage scenarios and it was similar for both countries (mean E_{DL}: 0.86 Vm^{-1} [IQR=0.26 Vm^{-1}] in FR and 0.80 Vm^{-1} [IQR=0.55 Vm^{-1}] in NL). Variations in total exposure in the different scenarios were mainly due to differences in the UL and TDD contributions, which were the highest for the file upload scenarios. UL exposure was notably higher in NL in comparison to FR (mean E_{UL} across all scenarios: 0.91 Vm^{-1} [IQR=0.64 Vm^{-1}] in NL vs 0.49 Vm^{-1} [IQR=0.38 Vm^{-1}] in FR), whereas TDD exposure was considerably higher in FR compared to NL (mean E_{TDD} across all scenarios: 0.38 Vm^{-1} [IQR=0.30 Vm^{-1}] in FR vs 0.14 Vm^{-1} [IQR=0.03 Vm^{-1}] in NL).

According to the 5G Scientist data (Figure 3), 4G-LTE was the most commonly used technology by the serving cell, representing 80.6% of the aggregates in FR (n=279) and 90.6% in NL (n=668). 5G-NR was observed as the serving cell technology in 16.2% of aggregates in FR (n=56) and 6.8% in NL (n=50). Only a small percentage of serving cells, 3.2% (n=11) in FR and 2.6% (n=19) in NL, employed 3G-WCDMA or earlier legacy technologies, particularly during voice calls using native phone services (i.e. 4G-nativeCall usage scenario). Due to the limited sample size, no further analysis could be conducted using the WCDMA data. In scenarios where the operational technology was constrained up to 5G, the serving cell employed 5G-NR technology in 37.6% of cases in FR and 18.3% in NL, which was observed to be non-standalone in both countries. In NL, only one network provider (Vodafone) supplied 5G-NR technology; however, no 3.5 GHz bands were observed. Given the early phase of 5G-NR

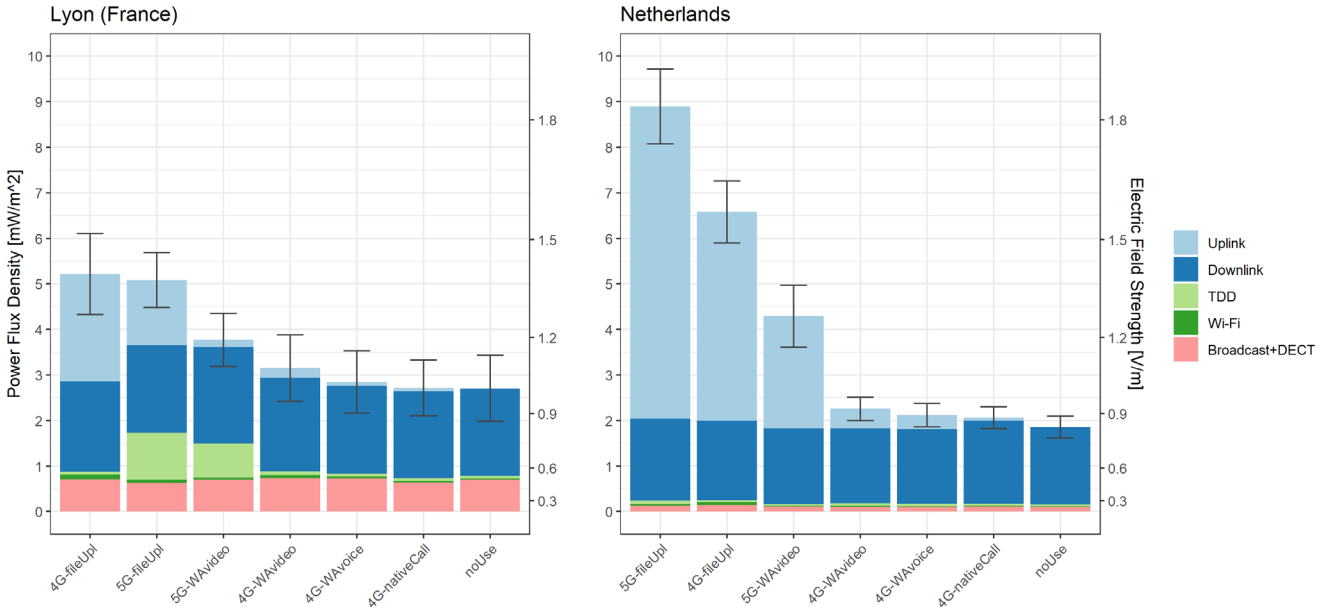

Figure 2. Mean exposure measured with the ExpoM-RF4 across all locations in each country by usage scenario. The colours indicate the contribution of each source category; the whiskers represent standard errors.

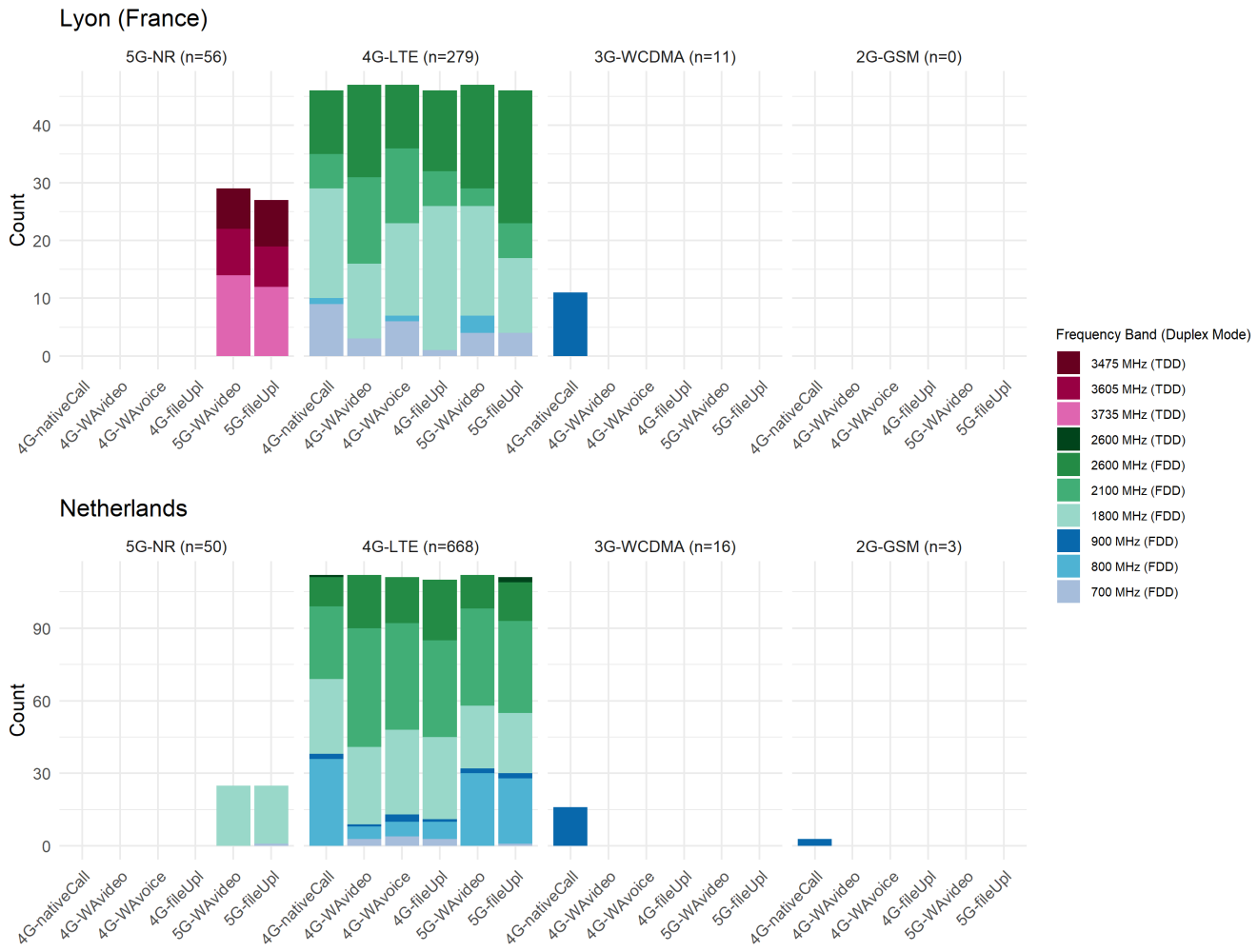

Figure 3. Distribution of operating frequency bands of the serving cell across usage scenarios and cellular technologies.

deployment in the Netherlands, 5G conversion functions were not analysed with the measurements conducted there. In both countries, a majority of operating frequency bands were observed in high-end frequencies, particularly of Frequency Division Duplex (FDD) type: 1800 MHz FDD (n=93 [26.9%] in FR, n=232 [31.5%] in NL), 2100 MHz FDD (n=49 [14.2%] in FR, n=241 [32.7%] in NL), 2600 MHz FDD (n=93 [26.9%] in FR, n=108 [14.7%] in NL). TDD and low-end FDD bands were observed less frequently (Figure 3).

In France, LTE-RSRP values varied between -116 to -57 dBm, with a median of -95 dBm, while LTE-RSSI values ranged from -101 to -52 dBm, with a median of -82 dBm (Figure 4). Comparatively, in the Netherlands, LTE-RSRP values varied between -116 to -59 dBm, with a median of -91 dBm, while LTE-RSSI values ranged from -103 to -51 dBm, with a median of -80 dBm. NR-ssRSRP values were observed between -118 to -79 dBm in France and -110 to -67 dBm in the Netherlands, with median values of -94 and -89 dBm, respectively. The cumulative distribution functions (CDFs) of most SSIs were close to a Gaussian distribution (Figure 4). Notably, in France, signal strength values above -70 dBm were less likely to occur compared to the Netherlands, indicating overall poorer signal quality in the Lyon selected locations. The CDFs did not indicate large variation between mobile phone models, but the distributions varied considerably between telecommunication providers (Figures S2–S5 in Extended Data[30]). Additionally, when using the Samsung S22+ model in France, LTE-RSSI values were recorded for only 12 of the aggregates, but these values appeared implausible and were therefore excluded from further analysis. Furthermore, NR-ssRSRP values were not recorded at all using Samsung S22+ model in France. In all locations, LTE-RSRP and LTE-RSSI were found to be strongly positively correlated with each other (tau=0.89 with p-value <0.001 in FR, and tau=0.85 with p-value <0.001 in NL).

Table 4 displays summary statistics of the peak EMF exposure at the right ear for voice call and file upload scenarios, and provides a similar summary for peak exposure at the chest for file upload scenarios. On average, exposure at the ear during voice call scenarios exceeded that of file upload scenarios due to the direct placement of the phone against the ear. Exposure levels from the handset were higher at the chest than at the ear for both 5G and 4G file upload scenarios, with slightly higher levels observed for 4G compared to 5G. Additionally, data throughputs were higher in 5G compared to 4G file upload scenarios, with a median of 1.59 Mbps (IQR: 1.46) for 4G versus 1.75 Mbps (IQR: 2.04) for 5G ear exposure aggregates, and a median of 4.87 Mbps (IQR: 3.07) for 4G versus 5.31 Mbps (IQR: 3.95) for 5G in chest exposure aggregates.

Far-field conversion functions

The regression estimates for the different far-field conversion functions are shown in Table 5. In the technical conversion models of both countries, sLTE-RSSI was found to be a significant predictor of DL active-band exposure (Likelihood Ratio Test (LRT) p-values <0.001), see Figure 5. The technical conversion models accounted for 41% (NL) and 45% (FR) of the variance in the data, with Root Mean Square Error (RMSE) of 0.28 for FR and 0.21 for NL. Additionally, Root Mean Square Logarithmic Error (RMSLE) values were 8.05 for FR and 7.42 for NL.

Figure 6 shows the relationship between all LTE-RSSI values of the own provider and 4G-LTE DL exposure from all

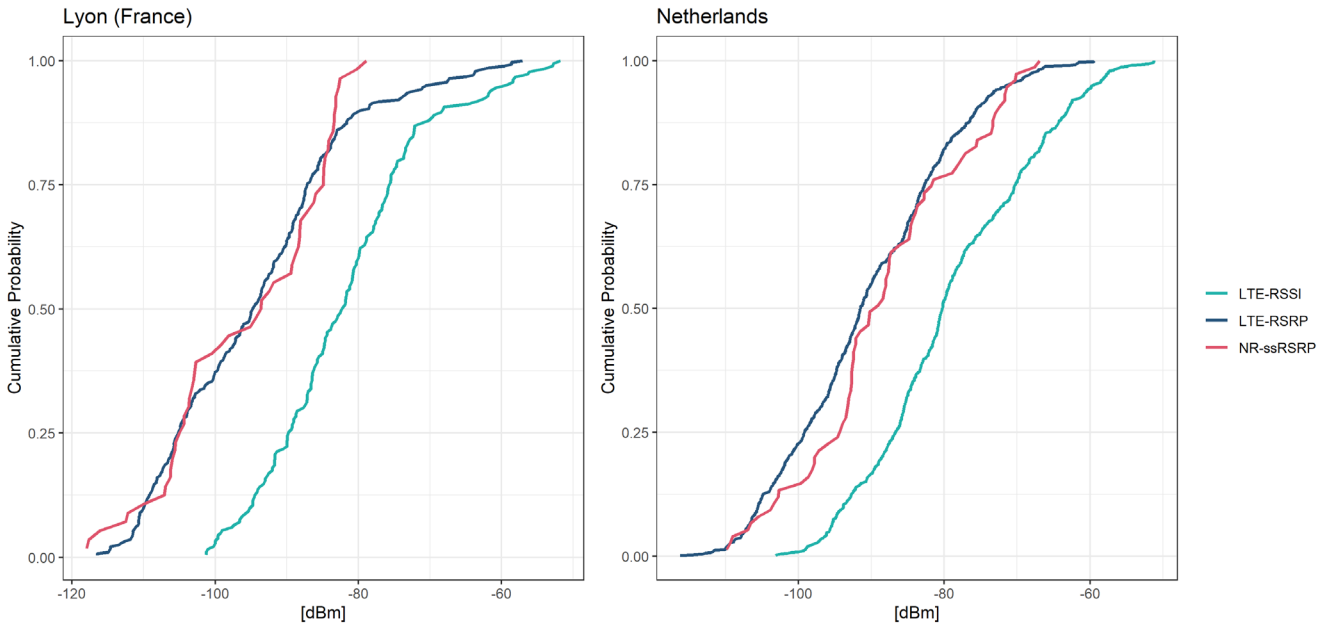

Figure 4. Cumulative distribution functions of the signal strength indicators measured with the 5G Scientist app.

Table 4. Summary statistics of peak EMF exposure at the ear and chest measured with the on-body electric field probes by usage scenario. Data from the Netherlands.

	Exposure from the handset measured at the right ear				Exposure from the handset measured at the chest	
	4G-nativeCall	4G-WAvoice	4G-fileUpl	5G-fileUpl	4G-fileUpl	5G-fileUpl
	[V m^{-1}]	[V m^{-1}]	[V m^{-1}]	[V m^{-1}]	[V m^{-1}]	[V m^{-1}]
Min.	0.81	1.06	1.42	1.63	2.06	2.03
1st Quartile	2.58	3.12	1.90	1.81	2.49	2.33
Median	3.85	4.65	2.44	2.17	3.57	2.98
Mean	6.63	7.07	2.49	2.23	3.69	3.56
3rd Quartile	8.41	7.88	2.80	2.58	4.25	3.75
Max	15.40	16.30	3.71	2.78	6.01	6.88
IQR	5.83	4.76	0.90	0.77	1.76	1.42
N	36	28	10	11	13	17

Table 5. Regression estimates for far-field conversion functions.

Far-field function	β_0* (95% CI)	β_1** (95% CI)
Technical conversion		
France	154.90 (145.99 - 163.82)	0.67 (0.56 - 0.78)
Netherlands	146.63 (142.57 - 150.70)	0.55 (0.50 - 0.60)
App conversion		
France	158.61 (150.14 - 167.08)	0.63 (0.53 - 0.74)
Netherlands	150.11 (146.20 - 154.03)	0.51 (0.46 - 0.56)
Map conversion		
France	171.72 (146.70 - 196.74)	0.91 (0.55 - 1.28)
Netherlands	185.30 (176.38 - 194.22)	1.09 (0.96 - 1.22)

*Estimated intercept (in dBm) from log-linear regression analyses.

**Estimated coefficient for the normalised LTE-RSSI value (in dBm) from log-linear regression analyses.

95% CI=95% confidence intervals.

providers. In the app conversion models, aLTE-RSSI was found to be log-linearly related to total DL exposure for 4G-LTE technology (LRT p-values <0.001). The fitted models explained 44% of the variance in FR and 37% in NL, with corresponding RMSE values of 0.55 and 0.45, and RMSLE values of 7.57 and 7.12, respectively. Compared to the technical conversion function, the app conversion models demonstrated lower performance in predicting DL exposure based on SSIs. Total DL exposure at a given location was influenced by base station density and proximity, reflecting geographic variations in cellular network infrastructure. Thus, DL exposure measured with the ExpoM-RF4 exhibited relatively low variability within a location, but high variability between locations (Figure 6). In contrast, LTE-RSSI data exhibited substantial variability within each location (Figure 6), since base stations from different providers are not evenly distributed across all areas and RSSI from a single network provider shows more variability over time than the aggregated exposure from multiple providers. Including an interaction term for the network provider improved the model performance (Figure S6 in Extended Data[30]).

Figure 7 shows the correlation between the sum of the average LTE-RSSI values of all network providers and the average 4G-LTE DL exposure at each location. Aggregating data by location revealed that the cumulative mean aLTE-RSSI from all

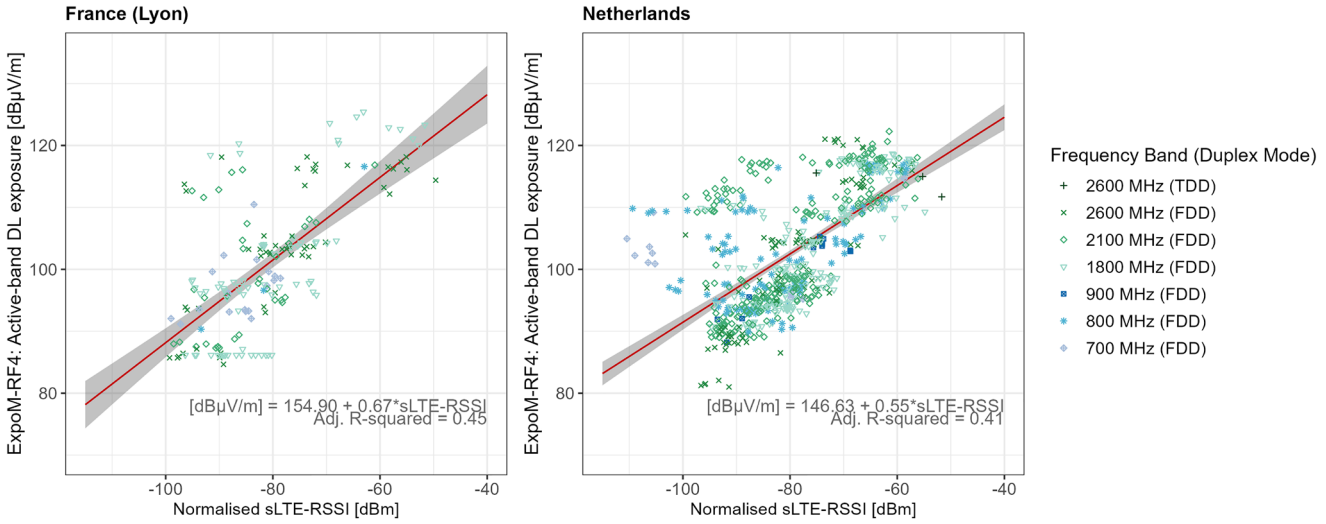

Figure 5. Regression analysis of active-band downlink field strength vs normalised LTE-RSSI from serving cell. The dots represent measurement aggregates (two-minute aggregates subdivided by registered cells) colour- and shape-coded according to frequency band. The red lines show the regression fit, and the grey areas represent 95% confidence bounds.

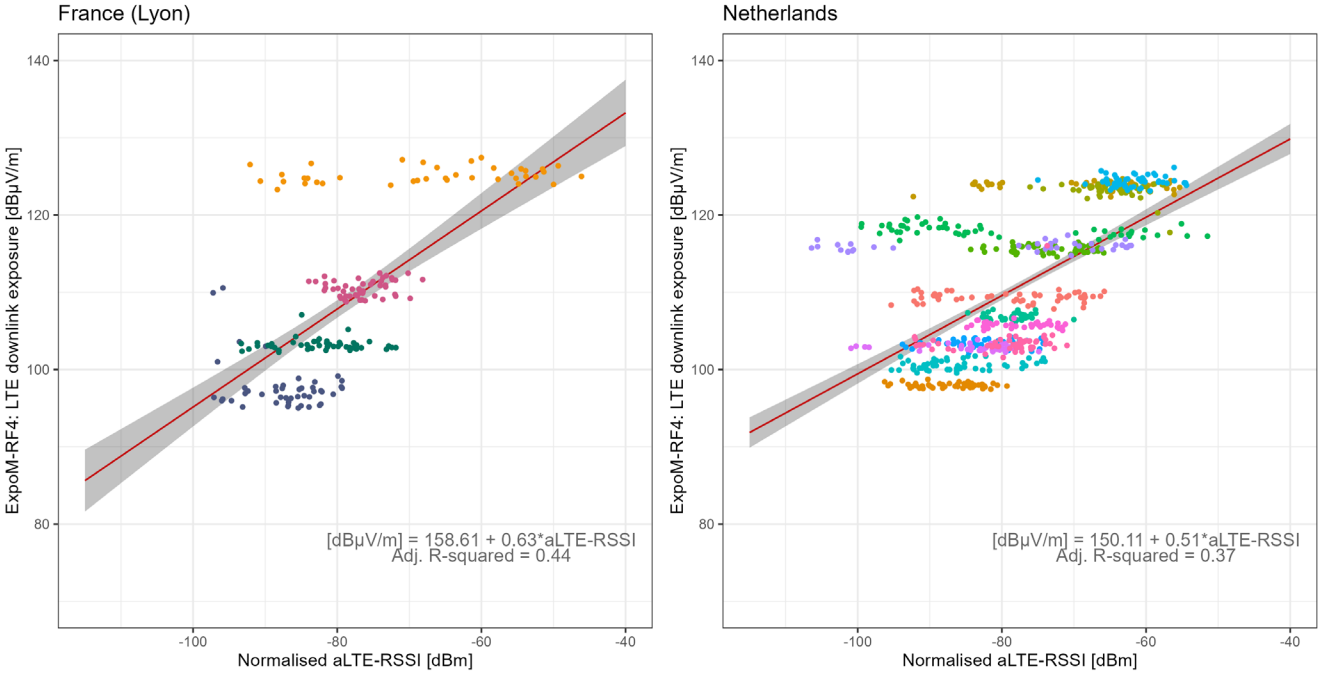

Figure 6. Regression analysis of LTE downlink field strength vs normalised LTE-RSSI from serving and neighbouring cells. The dots represent measurement aggregates (two-minute aggregates subdivided by registered cells) colour-coded by location, the red lines show the regression fit, and grey areas represent the 95% confidence bounds.

providers was a strong predictor of LTE downlink exposure (LRT p-values of 0.008 in FR and <0.001 in NL). For outdoor locations, aLTE-RSSI correlates positively with network density. The map conversion models explained over 95% of the variance in both countries, with RMSE values of 0.06 in FR and 0.14 in NL, and RMSLE values of 1.26 in FR and 1.64 in NL. Notably, the coefficients for aLTE-RSSI in both countries were remarkably similar in magnitude, adding to the robustness

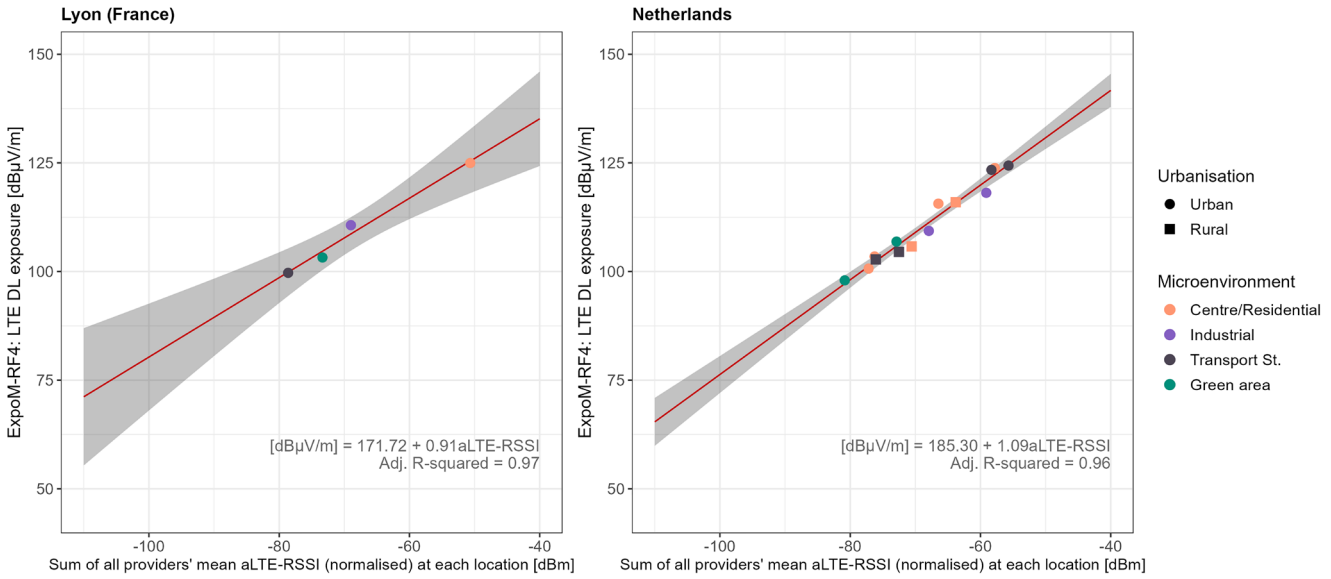

Figure 7. Regression analysis of mean LTE downlink field strength vs. providers' combined normalised aLTE-RSSI by location. The dots represent location aggregates, shape-coded by urbanisation and colour-coded by type of microenvironment. The red lines show the regression fit, while grey areas represent the 95% confidence bounds.

of the map function. The map conversion functions outperformed both technical and app functions, implying that while SSI values may serve as effective predictors of DL exposure on average, they may not accurately reflect instantaneous exposure levels.

Using LTE-RSRP instead of LTE-RSSI produced similar results for the technical, app, or map conversion functions (Figures S7–S9 in Extended Data[30]). On average, coefficient estimates for LTE-RSRP were weaker and models typically exhibited worse performance than those using LTE-RSSI. Additionally, the results of the far-field conversion function for 5G-NR showed that NR-ssRSRP was not a significant predictor of neither active-band nor NR exposure, which was always from a TDD band (Figure S10 in Extended Data[30]).

Near-field conversion functions

Figure 8 illustrates the relationship between sLTE-RSSI and exposure from the smartphone at the ear and chest. The regression estimates for the near-field conversion functions at the ear and chest are shown in Table 6. LTE-RSSI from the serving cell exhibited a negative log-linear relation with ear exposure from the handset, either during voice call scenarios or file upload scenarios (LRT p-values <0.001). The relationship between sLTE-RSSI and chest exposure was weaker but displayed the same directional trend (LRT p-value of 0.020). The observed relationship between $E_{UL\text{–}ActiveBand}$ measured with the ExpoM-RF4 and sLTE-RSSI also supports these findings (Figure S11 in Extended Data[30]).

Discussion and study insights

This paper presents a measurement protocol designed to derive functions that convert signal strength indicators recorded with the ETAIN 5G Scientist app into RF-EMF exposure proxies. The protocol concept focuses on capturing the spectrum of dependencies in the assessment of the relationship between signal strength indicators and RF-EMF exposure from mobile phone use. Such dependencies include type of telecommunication technology, power ranges, network loads, phone models, network providers and usage patterns.

By establishing links between validated RF-EMF measurement methods and app-generated data, we were able to demonstrate that the 5G Scientist app can be implemented as a practical tool for collecting RF-EMF exposure proxies. Our findings reveal that aggregated SSI data from different network providers, strongly correlates with exposure from base station antennas, which is in line with feasibility studies conducted by Fröhlich *et al.*[19], Schießl *et al.*[20], and Lopez-Espi *et al.*[21]. Among the SSIs, LTE-RSSI emerged as the most suitable proxy for far-field RF-EMF exposure from telecommunication technologies, as it encompasses a wide array of signal contributions, including both reference and interference signals[30].

Several sources of uncertainty must be acknowledged, as they may affect the confidence interval and validity of our conversion functions. In the technical conversion function (Figure 5), one major source of uncertainty arises from the fact that the ExpoM-RF4 does not capture cell-specific signals but rather measures exposure from all contributing sources within each DL frequency band. This introduces variability, particularly at lower RSSI values, where measured exposure is more likely to be influenced by signals from other cells and users operating on the same frequency band. In contrast, at higher RSSI values, the measured exposure is more likely dominated by the serving cell's signal, which is closer to what we want to predict

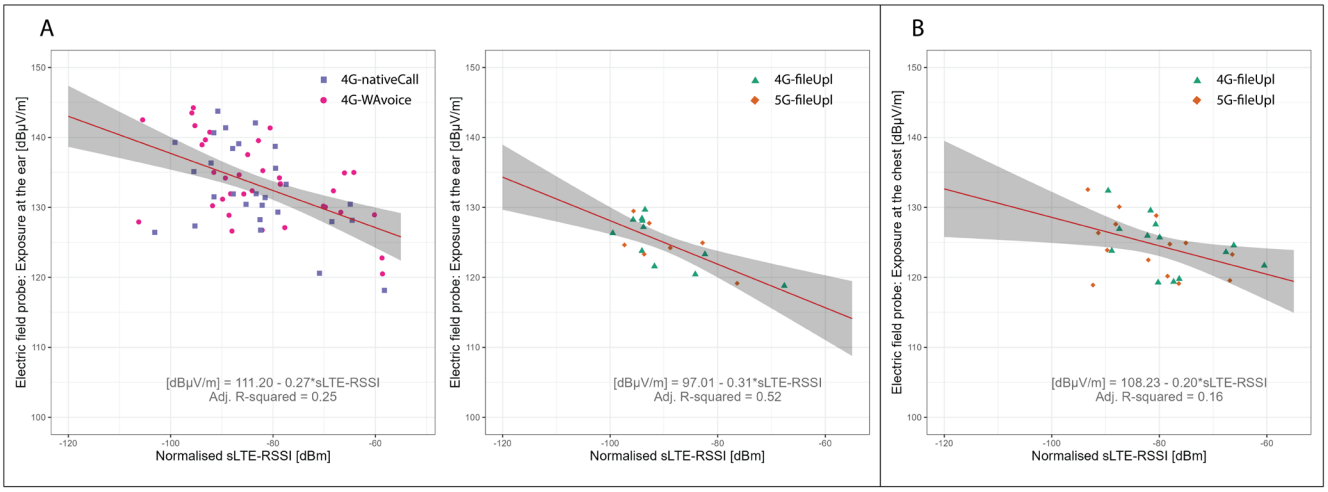

Figure 8. Regression analysis of handset-related EMF exposure at ear (A) and chest (B) vs LTE-RSSI. Regression analyses were stratified by phone positioning towards the ear (4G native and WhatsApp call scenarios) and in front of the body (file upload scenarios). The dots represent measurement aggregates (two-minute aggregates subdivided by registered cells) colour- and shape-coded by usage scenario. The red lines show the regression fit, while the grey areas represent the 95% confidence bounds. Data from the Netherlands.

Table 6. Regression estimates for near-field conversion functions.

Near-field function	β_0* (95% CI)	β_1** (95% CI)
Ear exposure		
Voice call scenarios	111.20 (101.81 – 120.60)	-0.27 (-0.37 - -0.15)
File upload scenarios	97.01 (83.52 – 110.50)	-0.31 (-0.46 - -0.16)
Chest exposure		
File upload scenarios	108.23 (94.64-121.82)	-0.20 (-0.37 - -0.03)

*Estimated intercept (in dBm) from log-linear regression analyses.

**Estimated coefficient for the normalised LTE-RSSI value (in dBm) from log-linear regression analyses.

95% CI=95% confidence intervals.

using the technical calibration function. Similarly, a significant source of uncertainty in the app conversion function stems from relying on a single provider's data to estimate total DL exposure (Figure 6). At a given location, a user may experience poor signal quality from their own provider, resulting in low received power, while total DL exposure could still be high due to stronger power contributions from other providers' base stations in the vicinity. This limitation introduces substantial uncertainty when estimating instantaneous exposure, which is why its implementation within the app was not pursued. Instead, we opted to provide an exposure estimate based on the technical conversion function, reflecting the user's own cellular network. Incorporating data from multiple network providers, as demonstrated in the map conversion function (Figure 7), improves the reliability of exposure estimates and addresses some limitations of both the technical and app conversion functions. Finally, while our methodology accounts for wavelength as a factor influencing the relationship between received power and measured RF-EMF exposure, it assumes constant antenna gains. In reality, antenna gains vary due to factors such as device orientation and the environment, introducing additional uncertainty in exposure estimation.

In Europe, the limited deployment of 5G-NR restricts our current conversion functions largely to 4G-LTE. Nevertheless, our study provides initial findings regarding the complex relationship between RF-EMF exposure and SSIs within the framework of 5G-NR technology. In TDD systems, where DL and UL transmissions occur simultaneously, the relationship between network quality and exposure becomes intricate. While better network quality may result in higher DL exposure due to stronger signal strength levels and closer proximity to base station antennas, it could conversely lead to reduced UL exposure. Better connectivity implies more efficient data transmission pathways with lower propagation loss and reduced interference, requiring less power from the mobile phone to

transmit data. As the rollout of 5G-NR technology progresses across Europe, future measurement campaigns will provide additional insights into the relationship between SSIs and RF-EMF exposure in TDD systems.

We gathered data on EMF exposure at two body locations (ear and chest) during typical mobile phone use scenarios, observing different patterns of attenuation as EMF signals propagate from the handset to the user's body. For instance, exposure at the ear was approximately three times lower when the phone was held in front of the body compared to when it was in direct contact with the ear. Our results suggest that SSIs may serve as proxies for peak exposure from the handset. We found that exposure from one's own device decreases in both strength and duration with increased signal quality, aligning with the power control mechanisms of the phone[12,14,35]. This result highlights the potential of SSIs as a useful metric for estimating handset-related EMF exposure.

Data from the pre-test and pilot studies was used to develop far-field and near-field conversion functions, which are going to be integrated into the first public 5G Scientist app version. These functions aim to provide users with exposure indicators associated with mobile phone use. Employing smartphones for RF-EMF exposure estimation offers a range of practical advantages. Capitalizing on the widespread use of smartphones in the population allows the collection of extensive datasets from diverse individuals and large geographical areas. This enhances the feasibility of conducting large-scale studies and opens avenues for robust epidemiological research on potential health effects linked to RF-EMFs. Moreover, the use of smartphones in exposure assessment aligns with the principles of citizen science, empowering individuals to actively contribute to research initiatives. This engagement not only fosters a sense of public participation but also enhances the transparency and inclusivity of scientific investigations.

Protocol changes

The feasibility of the measurement protocol was successfully demonstrated in the pre-test and pilot studies, providing insights into the conversion functions and identifying areas for improvement in future measurement campaigns. Our data was somewhat scarce at the lower end of the received signal strength range (i.e., more negative values) where signal quality deteriorates. Capturing the full range of signal strength values is particularly important for the near-field conversion function, as power control mechanisms should reflect a capped maximum exposure with decreased signal strength beyond a certain threshold[36]. In our pre-test and pilot studies, power control mechanisms for weak or very weak signal strengths were not fully achieved. Furthermore, more information is needed for low-end frequency bands (20% or less of the data recorded with the app during the pilot study corresponded to frequency bands of 900 MHz or lower). Therefore, to assess the full range of signal strength values in each study area, we have opted to expand measurements in indoor settings and add mobile measurements. For indoor locations selected in urban areas, additional measurements are going to be conducted at different indoor levels, including rooftops and basements.

Mobile measurements will be conducted in both urban and rural areas. In urban and rural settings, polygonal measurement zones, ranging from 0.5 to 1 km^2 each, will be defined. Trained researchers will simultaneously take recordings using the 5G Scientist app with the smartphones set to idle mode (i.e. not actively being used) and the ExpoM-RF4 device, while walking along the roads within the polygonal zones and while travelling by public transport between the zones. The smartphones will be carried in front of the body inside a pouch, whereas the ExpoM-RF4 will be stored in a backpack with appropriate outer compartments, maintaining a minimum distance of 30 cm from the researcher's body to prevent body-shielding effects.

Drawing from the experience gained through the pre-test and pilot studies, we have identified the most critical methods for a shortened version of the protocol to be applied in other European countries. We observed negligible variance in signal strength distributions across the tested phone models. Consequently, we decided to standardize measurements using only the Samsung A22 phone. Additionally, spot measurements will focus only on the following usage scenarios: non-use, 4G native voice call, 4G file upload, and 5G file upload. Video call scenarios were removed from the protocol as they rarely exhibited EMF exposure above the detection limits of the electric field probes. Collectively, these changes significantly reduce the protocol's length, enabling broader implementation across multiple countries without compromising the utility of the data for deriving conversion functions.

Conclusions

The implementation of the measurement protocol in pre-test and pilot studies demonstrated its suitability for deriving functions to convert continuously collected signal strength indicators with an open-access smartphone app into electric field values. The findings from these studies underscore the necessity of expanding the protocol to include additional indoor and mobile measurements, enabling the capture of a broader range of signal strength values. Analysis of the pre-test and pilot studies revealed a positive log-linear relationship between far-field RF-EMF exposure and signal strength values, indicating that better signal quality correlates with higher levels of downlink RF-EMF exposure. When SSI data was aggregated by location, we found a strong correlation with far-field exposure, with estimated regression coefficients for the normalised LTE-RSSI value of 0.91 (95% CI: 0.55 - 1.28) in FR and 1.09 (95% CI: 0.96 - 1.22) in NL. Conversely, a negative log-linear trend was observed between EMF exposure from the handset and signal strength values, with estimated coefficients for the normalised LTE-RSSI value of -0.31 [95% CI: -0.46 - -0.16] for ear exposure and -0.20 [95% CI: -0.37 - -0.03] for chest exposure during file upload scenarios. This suggests that the app data could serve as a surrogate for exposure from the handset. Nevertheless, further data collection and analysis are needed to reduce uncertainty and improve the accuracy of exposure estimates.

Ethical and consent

Ethics and consent were not required.

Data availability

Underlying data

The dataset used in this study is available at the Yoda data publication platform from Utrecht University: *Dataset for publication: Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study to derive conversion functions. DOI:* https://doi.org/10.24416/UU01-OXUHTC

This study contains the following underlying data:

- "Data" folder (Contains the raw and processed data used in the analysis).
    - Scenarios_FR.csv and Scenarios_NL_phone_locID_yyyymmdd.csv → Raw dataset containing the information collected using the ETAIN-scenarios app, including timestamps for each usage scenario. The naming convention for the files includes the country ("_NL_" or "_FR_"), the phone used to collect the data ("_phone_"), the location identifier ("_locID_"), and the date ("_yyyymmdd").
    - Etain_CELL_NL_phone_yyyymmdd_hhmmss.csv and Etain_CELL_FR_phone_yyyymmdd_hhmmss.csv → Raw data from ETAIN 5G Scientist app for Netherlands and France. The naming convention for the files includes the country ("_NL_" or "_FR_"), the phone used to collect the data ("_phone_"), the date ("_yyyymmdd_") and time ("_hhmmss") of data collection.
    - Expom_yyyymmdd_hhmmss.csv → Raw data from ExpoM-RF4 exposimeter. The naming convention for the files includes the date ("_yyyymmdd_") and time ("_hhmmss") of data collection.
    - Expom_yyyymmdd_hhmmss_corr.csv → Cross-talk corrected data from ExpoM-RF4 exposimeter. The naming convention for the files includes the date ("_yyyymmdd_") and time ("_hhmmss") of data collection.
    - ProbeLog1_NL_locID_yyyymmdd.csv → Raw data collected with the on-body electric field probe placed at the right ear. The naming convention for the files includes the country ("_NL_"), the location identifier ("_locID_"), and the date ("_yyyymmdd") of data collection.
    - ProbeLog2_NL_locID_yyyymmdd.csv → Raw data collected with the on-body electric field probe placed at the chest. The naming convention for the files includes the country ("_NL_"), the location identifier ("_locID_"), and the date ("_yyyymmdd") of data collection.
    - SCENARIOS_data.rds → Processed dataset from ETAIN-scenarios app.
    - ETAIN_CELL_data.rds → Processed dataset from ETAIN 5G Scientist app.
    - ETAIN_CELL_sc.rds → Processed dataset combining ETAIN-scenarios (SCENARIOS_data.rds) and ETAIN 5G Scientist (ETAIN_CELL_data.rds) data. The dataset include app data by unique combination of location, phone, network provider, and scenario.
    - EXPOM_data.rds → Processed dataset from ExpoM-RF4 exposimeter.
    - EXPOM_sc.rds → Processed dataset combining ETAIN-scenarios (SCENARIOS_data.rds) and ExpoM-RF4 data (EXPOM_data.rds). The dataset include ExpoM-RF4 data by unique combination of location, phone, network provider, and scenario.
    - PROBE_data.rds → Processed dataset from on-body electric field probes.
    - PROBES_sc.rds → Processed dataset combining ETAIN-scenarios (SCENARIOS_data.rds) and electric field probes data (PROBE_data.rds). The dataset include probe data by unique combination of location, phone, network provider, and scenario.
    - etain_allDL_nl.rds and etain_allDL_fr.rds → Mean aggregates dataset from 5G Scientist, ExpoM-RF4, and probes for far-field analysis (Netherlands and France).
    - etain_allUL_nl.rds → Mean aggregates dataset from 5G Scientist, ExpoM-RF4, and probes for near-field analysis (Netherlands and France).
- "Data_codebooks" folder (Documentation of the dataset variables, including definitions, units, and data types).
- "Scripts" folder (RScripts used for data processing, analysis, and visualization).

Data is publicly available under the Creative Commons Attribution 4.0 International License. Users are free to share, adapt, and use the dataset, provided appropriate credit is given.

Extended data

Yoda data publication platform from Utrecht University: *Dataset for publication: Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study*

to derive conversion functions. DOI: https://doi.org/10.24416/UU01-OXUHTC

This study contains the following extended data:

- ExtendedData.pdf (tables and figures with direct link to the main text)
- STROBE_checklist.pdf (see Reporting guidelines section)

Software availability

This study used the following open-source software:

- QGIS for location visualisation and selection. Available at: http://qgis.org
- R for data analysis within the RStudio environment. Available at: https://www.r-project.org/ and https://posit.co/

R scripts used for data cleaning and analysis are available on the Yoda data publication platform from Utrecht University. These scripts ensure that all data processing steps can be replicated and verified. The dataset and scripts can be accessed at:

- Dataset for publication: *Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study to derive conversion functions.* DOI: https://doi.org/10.24416/UU01-OXUHTC

Reporting guidelines

This study was conducted in accordance with the STROBE guidelines for observational studies. The checklist is included in the Extended Data, available on the Yoda data platform hosted by Utrecht University: *Dataset for publication: Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study to derive conversion functions.* DOI: https://doi.org/10.24416/UU01-OXUHTC

Acknowledgements

The authors would like to thank Timon Schmid, who implemented the native Android kernel for the ETAIN 5G Scientist App and adapted the mobile phone application to implement the usage scenarios. The authors would like to thank Monika Moissonnier and Elsa Lubart (IARC/WHO) for their help in the data collection in Lyon (France). The development of the on-body electric field probe was funded by the Research Foundation for Electricity and Mobile Communication (FSM, Zurich, Switzerland). Where authors are identified as personnel of the International Agency for Research on Cancer/World Health Organization, the authors alone are responsible for the views expressed in this article and they do not necessarily represent the decisions, policy or views of the International Agency for Research on Cancer/World Health Organization.

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✔

Pablo Luis López Espí
University of Alcalá, Alcalá de Henares, Spain

Many thanks to the authors for their response to my previous suggestions.
I believe that at this stage the proposal can be accepted

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Microwave and Antennas, EMF Measurements

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 08 May 2025

https://doi.org/10.21956/openreseurope.21367.r52702

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?

Dirk Heberling
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Christian Bornkessel
RF and Microwave Research Group, Technical University Ilmenau, Ilmenau, Germany

The paper describes a method for determining conversion factors in order to draw conclusions about the strength of the electric field in which the phone is located from parameters read out with a software-modified cell phone (in particular RSRP, RSSI). The investigations are described in a comprehensible manner. They are very extensive; in particular, measurements were carried out at

four locations in Lyon and 14 locations in the Netherlands, each with three cell phones, several network operators and ten different usage scenarios. A common conversion factor for far-field exposure was aggregated from the measurements by averaging over all frequencies, cell phones, locations and network operators; values for ear and chest exposure were derived for near-field exposure from the user's own cell phone.

Our studies, cited as [20] in the document, had shown, that direct calibration measurements of the mobile phones in comparison to frequency and code-selective measuring devices for electromagnetic fields, e.g. the Narda SRM-3006, for each mobile and frequency band separately, result in much more accurate conversion factors. Beside of this our studies showed a very rough measurement discretisation of the mobile and a quite low upper dynamic rage. So strong field strength, which are of great interest, cannot be evaluated using the RSSI, because the maximum range is reached already. In our view an alternative for LTE, 5G and UMTS can be to measure the field strengths code-selectively at a measurement location by the load-independent signalling channels (RS0...RS3 for LTE, SSS for 5G, CPICH for UMTS) and link them to the corresponding SSI values of the cell phone (LTE_X_rsrp, NR_X_ssRSRP and WCDMA_X_rsrp). Compared to the procedure described in the paper, this would have the advantage that a correlation is made to the field strength that is specifically generated by these signalling signals and not to the field strength in the entire frequency band of the respective radio service, which also includes other operators. If a link is to be made with RSSI instead of RSRP, a channel power measurement is carried out in the downlink frequency band of the respective operator for the respective technology instead of the code-selective measurement. This results in conversion factors that are frequency-specific and mobile phone-specific. It is expected that these frequency-specific factors in particular will lead to a more accurate exposure assessment than factors that are averaged over all frequencies and cell phone types. This is because, strictly speaking, the conversion factor determined here by averaging over all frequencies can only be applied to networks that contain a similar frequency-related composition of the signal. If the proportional frequency composition changes, the conversion factor becomes increasingly inaccurate. It should be possible to take the frequency-specific factors into account in the app, as the frequency of the serving cell and the neighbouring cells is also included in each case.

Having on mind that 5G will be the future network standard, we consider the assessment of 5G MaMIMO as very important, which only plays a subordinate role in the current study due to the lack of availability of corresponding base stations: In our experience the read-out power value of SSS in the SSB signalling channel is not a suitable predictor for the exposure present, at least if the station has an appreciable utilization. This is due to the fact that with 5G, the share of signalling in the total exposure at full capacity is only about 1% in terms of power. In addition, to our knowledge and according to the information of some system technology manufacturers, the traffic beam designed for data transmission may have a significantly higher gain than the broadcast beam for signalling. A more suitable SSI would have to be found here, which may only be transmitted during an active connection. In this context, the question also arises as to why file uploads were taken into account in the usage scenarios, but not data-intensive file downloads, which can lead to a relevant utilization of the base station when downloading movies, for example.

In addition to these general comments, the following detailed questions arise:

In the introduction the authors mention, that “...UL exposure is self-induced, more localized, and originates from near-field sources situated within the Fraunhofer limit of the human body’s

position…" To our experience this is even more closed and should be considered as the zone of reactive nearfield.

The authors explained that they use the number of deployed antennas as a measure for the network density and used the network density as a measure for the network load. To our experience this is not very strong correlated as a base station on a rural environment might have a much higher load because it is the only one and many antennas are often not an indicator for a high network density.

In Figure 1 the starting frequency of the Expom-RF4 is give as 50Hz. To our knowledge it starts at 50 MHz.

In the chapter methods subchapter measurement tools the authors write"…refers to the specific cell within the network currently providing telecommunication services to the mobile phone." How are signals from specific cell identified and used? How are more advanced technologies like carrier aggregation identified and handled?

There is contradicting information about the frequency range of the on-body field sensors. Figure 1 mention 100Hz – 5.800MHz and on page 7 100 – 5.800MHz is given, which we would read as 100MHz – 5.800MHz.

For Figure 2 we recommend to use the same sequence of user scenarios for both graphs. It seemed that especially in France the traffic load was not very high in comparison to the no-use case. Does this really describe a worth case?

In our opinion the far-field conversion factor, as explained on page 12, should not depend on the country scenario but purely on the sensor type, in detail the frequency dependent antenna factor and calibration of the phone.

Is the rationale for, and objectives of, the study clearly described?

Yes

Is the study design appropriate for the research question?

Partly

Are sufficient details of the methods provided to allow replication by others?

Yes

Are the datasets clearly presented in a useable and accessible format?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Electromagnetic fields, antennas antenna measurement, eletromagnetic exposure, radar technology

We confirm that we have read this submission and believe that we have an appropriate level

of expertise to confirm that it is of an acceptable scientific standard, however we have significant reservations, as outlined above.

Reviewer Report 25 April 2025

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Leonidas Gavrilas
University of Ioannina, Ioannina, Greece

Full Review Report

Summary of the Article
The article by Sandoval-Diez et al., titled “Determining the relationship between mobile phone network signal strength and radiofrequency electromagnetic field exposure: protocol and pilot study to derive conversion functions”, describes a comprehensive study protocol and initial pilot studies aimed at developing reliable formulas for converting mobile phone network signal strength indicators (SSIs) into estimates of radiofrequency electromagnetic field (RF-EMF) exposure. The researchers developed an open-access smartphone application, "ETAIN 5G-Scientist." They systematically evaluated its performance in estimating RF-EMF exposure by comparing app-generated data with precise measurements obtained from a professional exposimeter (ExpoM-RF4) and wearable on-body electric field probes.

The study occurred in various locations in France and the Netherlands and tested different smartphones, mobile network providers, and usage scenarios (e.g., voice calls, video streaming, data uploads). The authors found a log-linear relationship between LTE signal strength indicators and far-field RF-EMF exposure. In contrast, near-field handset-related exposure showed a negative correlation with SSIs. The findings suggest considerable potential for using smartphone apps for large-scale and citizen-involved scientific assessments of RF-EMF exposure. However, the authors note that further data collection and analysis are necessary to address uncertainties and enhance accuracy.

Evaluation and Specific Comments
Below are the evaluations addressing specific aspects of the manuscript:
1. Clarity of Rationale and Objectives
Answer: Yes, clearly described.
The rationale and objectives of the study were very clearly defined. The authors effectively contextualized their work within the growing complexity of modern mobile communication technologies and the current methodological limitations of measuring RF-EMF exposure. They convincingly explained their choice of developing smartphone-based solutions as a feasible and scalable alternative. Objectives were explicitly outlined, clearly stating the goal to establish relationships between network SSIs and RF-EMF exposure, thus facilitating future large-scale epidemiological studies.

2. Appropriateness of Study Design
Answer: Yes, appropriate.
The study design was well-structured and appropriate for addressing the research question. Standardized usage scenarios and professional RF-EMF measurement tools alongside the smartphone app allowed rigorous and reliable comparisons. The authors carefully selected diverse environments (urban vs. rural, indoor vs. outdoor) and multiple phone models and network providers, ensuring representativeness and enhancing generalizability.

3. Replicability of Methods
Answer: Yes, fully replicable.
The methods were comprehensively detailed, sufficiently allowing replication. Explicit descriptions of location selection criteria, measurement setups, device specifications, data collection procedures, data analysis, and aggregation were provided. Extensive supplemental information further facilitated complete methodological transparency.

4. Accessibility and Presentation of Datasets
Answer: Yes.
The data presented were precise, well-summarized, and effectively supported the authors' conclusions through descriptive statistics, regression analyses, and graphical visualizations.

Paper Structure
1. Introduction and Objectives
The introduction of the paper effectively contextualizes the significance of the research, clearly explaining how rapidly evolving mobile communication technologies create challenges in accurately assessing radiofrequency electromagnetic field (RF-EMF) exposure. It introduces relevant concepts such as uplink and downlink exposure, emphasizing the need for innovative assessment methods due to technological advancements and existing limitations of conventional instruments. The authors highlight the advantages of leveraging smartphone technology for scalable, population-level exposure monitoring through citizen science approaches. However, the introduction could be improved by explicitly identifying specific gaps in previous research or indicating how current smartphone-based apps fall short of adequately estimating RF-EMF exposure. Clarifying the exact novel contributions of the ETAIN 5G-Scientist app compared to existing applications would strengthen the rationale. Overall, the objectives are explicitly stated, well-aligned with the research context, and sufficiently precise.

2. Methods – Spot Measurement Protocol
The methodological section is thorough and provides extensive details required for replication, including the criteria for selecting measurement locations, the setup of devices used (ExpoM-RF4 exposimeter, smartphones, on-body electric field probes), and clearly defined usage scenarios. The authors adequately justified their choices, detailing the differences in microenvironments (urban vs. rural, indoor vs. outdoor) and emphasizing standardization of usage scenarios. Nonetheless, the description could benefit from explicitly addressing practical challenges encountered during data collection, such as equipment malfunctions or environmental interference. Additionally, the synchronization approach between devices could be more clearly described, specifying precisely how temporal alignment was achieved and validated, to enhance replicability further.

3. Pre-test and Pilot Studies – Data Analysis and Modelling
The analytical approach adopted is well-suited to the research question, with comprehensive explanations on normalization methods, regression modelling, and data aggregation into two-minute intervals. The choice of log-linear regression for establishing conversion functions is appropriate and justified.

4. Results – Descriptive statistics, Far-field and Near-field Conversion Functions
The results section presents descriptive statistics supported by compelling visualizations. It provides valuable insights into signal strength indicators and RF-EMF exposure relationships, particularly the observed positive log-linear relationships for far-field exposure and negative log-linear relationships for near-field handset-related exposure. The regression analyses are reported, with explicit statistical parameters to evaluate model performance. However, the authors could improve this section by explicitly addressing potential outliers or extreme values in the data, detailing any sensitivity analyses conducted to ensure the robustness of the results. Moreover, explicitly acknowledging limitations arising from the relatively small sample sizes in some scenarios (particularly near-field measurements) would provide additional transparency and help contextualize findings more realistically.

5. Discussion and Study Insights – Protocol Changes
The discussion section provides valuable insights into the implications of the findings and identifies uncertainties inherent in the study. It outlines proposed protocol modifications, including expanded measurements in more diverse indoor environments and increased focus on low-frequency bands. This reflective approach significantly contributes to the manuscript's strength, offering clear future directions and practical improvements. However, the authors could deepen the discussion by explicitly addressing potential practical consequences of these protocol adjustments in terms of feasibility, costs, and resource implications. Furthermore, acknowledging explicitly any biases that might result from the methodological choices (e.g., selection of smartphone models, differences in infrastructure across locations) would enhance the discussion's comprehensiveness.

6. Conclusions
The conclusions are concise and effectively summarize the main findings, highlighting the potential of the smartphone app approach for large-scale RF-EMF exposure assessments. The authors correctly note that additional extensive measurements are necessary to refine and validate their conversion functions, offering a realistic appraisal of current limitations and future research requirements.

Final Conclusion
The article is overall scientifically rigorous, clearly written, and methodologically sound. It contributes to RF-EMF exposure assessment methodologies, particularly by leveraging citizen science and ubiquitous smartphone technology.

Is the rationale for, and objectives of, the study clearly described?

Yes

Is the study design appropriate for the research question?

Yes

Are sufficient details of the methods provided to allow replication by others?
Yes

Are the datasets clearly presented in a useable and accessible format?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Electromagnetic radiation perception and misconceptions, radiofrequency electromagnetic exposure, wireless communication systems, transmission and reception of RF signals, health-related attitudes toward EMR, scientific literacy in EMR. STEM education, educational robotics, ICT integration in learning environments, early childhood science education, environmental education.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 12 April 2025

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Rosa Orlacchio
IMS laboratory, University-École Pratique des Hautes Études (EPHE),, Paris, France

I thank the authors for their reply, and I have no further comments to make.

Is the rationale for, and objectives of, the study clearly described?
Yes

Is the study design appropriate for the research question?
Yes

Are sufficient details of the methods provided to allow replication by others?
Yes

Are the datasets clearly presented in a useable and accessible format?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Therapeutic bioelectromagnetics, experimental electromagnetic dosimetry

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Version 1

Reviewer Report 04 November 2024

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Pablo Luis López Espí
University of Alcalá, Alcalá de Henares, Spain

The proposal presents an interesting analysis of signal levels received with a mobile phone compared to existing field levels measured with a personal exposure meter. Two measurement locations are analysed in the manuscript: one in France and one in the Netherlands. Different scenarios are also analysed as a function of usage and technology. In the proposal, two essentially different quantities are being compared: The measured power of the control signals of the different technologies (RSCP, RSSI...) on a smartphone and the electric field strength of the exposure measured with an exposure meter.
Overall, the proposal is well presented and of scientific interest. However, some issues should be more clearly explained:
- The authors indicate that they do not know if any study has been carried out on this aspect, however, there is a recent reference (1) where the conversion between the two terms and some possible error factors are explained.
- Taking into account this conversion, if we assume linearity of both receivers in their full measurement range, the relationship presented in Eq1 as a linear regression should only remain as an offset term (Beta1=1) and perhaps this explains the poor values of R^2 in the fits in figures 5, 6 and 8 and, on the contrary, the goodness of fit in figure 7.
- It should also be explained in more detail how all the contributions detected by the smartphone have been agregated: sum of the dBm powers of the different signals of the same technology (e.g. sum of RSSI of the different BTS or operators to compare with the exposure meter value) or any other chosen method. If only the main operator is considered, this can lead to significant errors.
- The authors propose a 2-minute data aggregation. This raises several questions: How often have the signal levels been measured that give rise to this aggregation, why has this interval been chosen rather than the usual 6 minutes for averaging exposure data, how have the aggregated mobile and exposure meter measurements been synchronised, and is there the same amount of raw data in both sets of measurements?
- It is also worth asking about the aggregation of data whether the average is a representative value due to the temporal variability of the values detected by the mobile due to signal losses, multipaths, etcetera. Should we discard the lowest values in the same vay of that we discard losses in the smartphone?

- Another question to analyse is that the probe for on-body measurements has a lower detection limit of 2 V/m (page 9), which is a value far above the values measured with the exposure meter, so that the validity of the results obtained could be questioned. Could it be a typo?

References

1. López-Espí PL, Sánchez-Montero R, Guillén-Pina J, Castro-Sanz R, et al.: Smartphone-Based Methodology Applied to Electromagnetic Field Exposure Assessment.*Sensors (Basel)*. 2024; **24** (11). PubMed Abstract | Publisher Full Text

Is the rationale for, and objectives of, the study clearly described?

Yes

Is the study design appropriate for the research question?

Yes

Are sufficient details of the methods provided to allow replication by others?

Yes

Are the datasets clearly presented in a useable and accessible format?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Microwave and Antennas, EMF Measurements

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 24 Mar 2025

Nekane Sandoval-Diez

Review 2 by Pablo Luis López Espí (University of Alcalá, Alcalá de Henares, Spain)

Comment: The proposal presents an interesting analysis of signal levels received with a mobile phone compared to existing field levels measured with a personal exposure meter. Two measurement locations are analysed in the manuscript: one in France and one in the Netherlands. Different scenarios are also analysed as a function of usage and technology. In the proposal, two essentially different quantities are being compared: The measured power of the control signals of the different technologies (RSCP, RSSI...) on a smartphone and the electric field strength of the exposure measured with an exposure meter. Overall, the proposal is well presented and of scientific interest. However, some issues should be more clearly explained.

Answer: We sincerely appreciate the reviewer's insightful comments and constructive feedback, which have helped us improve our manuscript. Below, we provide detailed responses to each point raised.

Comment: The authors indicate that they do not know if any study has been carried out on this aspect, however, there is a recent reference (1) where the conversion between the two terms and some possible error factors are explained.
Answer: Thank you for pointing out this relevant publication. We have now included it in the introduction/discussion and referenced it accordingly.

Comment: Taking into account this conversion, if we assume linearity of both receivers in their full measurement range, the relationship presented in Eq1 as a linear regression should only remain as an offset term (Beta1=1) and perhaps this explains the poor values of R^2 in the fits in figures 5, 6 and 8 and, on the contrary, the goodness of fit in figure 7.
Answer: We agree that the performance differences between Figures 5, 6, and 8 versus Figure 7 highlight the impact of various sources of uncertainty of each model, leading to $\beta1<1$. These uncertainties are captured by the error term ε_i in Equation 1, and we have expanded our discussion to acknowledge and elaborate on these sources of uncertainty. Our goal was to empirically assess the relationship between SSI and exposure in real-world conditions, recognizing that a perfect match ($\beta1 = 1$) is unlikely due to inherent measurement uncertainties, environmental variability, and device-specific factors.

Comment: It should also be explained in more detail how all the contributions detected by the smartphone have been aggregated: sum of the dBm powers of the different signals of the same technology (e.g. sum of RSSI of the different BTS or operators to compare with the exposure meter value) or any other chosen method. If only the main operator is considered, this can lead to significant errors.
Answer: Thank you for this observation. We have now expanded the explanation of our aggregation method for the map conversion function, clarifying how signal contributions were combined.

Comment: The authors propose a 2-minute data aggregation. This raises several questions: How often have the signal levels been measured that give rise to this aggregation, why has this interval been chosen rather than the usual 6 minutes for averaging exposure data, how have the aggregated mobile and exposure meter measurements been synchronised, and is there the same amount of raw data in both sets of measurements?
Answer: Thank you for your observation. We have added more details on this aspect in the methods section. We chose a 2-minute data aggregation period because each usage scenario was designed to last for 2 minutes. This duration was selected to ensure the feasibility and practical applicability of the protocol. Since these were spot measurements, extending the measurement duration beyond 2 minutes would not have provided substantially more information. Furthermore, we did not apply the typical 6-minute averaging time or other guideline-based averaging periods, as the aim of the app was not to assess compliance with exposure guidelines but rather to characterize exposure under specific usage conditions. Regarding measurement frequency, SSI data from the app was recorded every second, while ExpoM-RF4 measurements were taken every 7 seconds. Both datasets included timestamps, which allowed us to synchronise them with each other and with the timestamps from the ETAIN-scenarios bespoke app used to log usage scenarios. This temporal alignment ensured consistency across the mobile app and exposimeter data for aggregation and analysis.

Comment: It is also worth asking about the aggregation of data whether the average is a representative value due to the temporal variability of the values detected by the mobile due to signal losses, multipath, etcetera. Should we discard the lowest values in the same way of that we discard losses in the smartphone?
Answer: We acknowledge that SSI values are subject to temporal variability due to signal losses, multipath effects, and other environmental factors. We chose to use the arithmetic mean SSI as it provides a stable representation of the signal strength experienced at a given location when connected to a certain cell. Additionally, the measurement devices have different sampling rates (ExpoM-RF4 measures exposure every 7 seconds, while the app logs SSI data every second). While percentile-based aggregation could be considered, it may not be as robust in this context due to the mismatch in sampling frequency. Using percentiles instead of averages could introduce additional uncertainty by comparing distributions with different granularities. To further assess this, we performed a sensitivity analysis using the 95th percentile aggregation instead of the average. The results did not materially change (see figure below for technical conversion function fitted using 95th percentile aggregates).

Figure 1- 18285 (OREU).docx

Figure 1. Regression analysis of active-band downlink field strength vs normalised LTE-RSSI from serving cell using 95th percentile values. *The dots represent measurement aggregates (two-minute 95th percentile aggregates subdivided by registered cells) colour- and shape-coded according to frequency band. The red lines show the regression fit, and the grey areas represent 95% confidence bounds.*

Comment: Another question to analyze is that the probe for on-body measurements has a lower detection limit of 2 V/m (page 9), which is a value far above the values measured with the exposure meter, so that the validity of the results obtained could be questioned. Could it be a typo?
Answer: Unfortunately, the lower detection limit of the field probes is indeed 2 V/m. Unlike the ExpoM-RF4, the probes used in this study are broadband and were specifically designed for on-body measurements, focusing on exposure from the handset. Exposure from near-field sources was expected to be orders of magnitude higher than far-field exposure when the phone is used close to the body. We acknowledge that the 2 V/m detection limit is a technical limitation of the probes. As noted in the paper, when limiting the analysis to measurements above this threshold, only a few measurements exceeded it, and for most usage scenarios, the exposure remained below this limit. Despite this, we were still able to observe the expected negative correlation between handset exposure and signal strength in our results.

Competing Interests: No competing interests were disclosed.

Reviewer Report 24 October 2024

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Rosa Orlacchio
IMS laboratory, University-École Pratique des Hautes Études (EPHE),, Paris, France

The authors outline the development and evaluation of the "5G Scientist Monitor," an open-access mobile app created within the frame of the EU project ETAIN to estimate radiofrequency electromagnetic field (RF-EMF) exposure from smartphones using different signal strength indicators (SSIs).

The paper is very interesting and well-written. Please, find below a few comments.

Abstract.
RSSI. If it is the R coefficient of the linear regression I would express it as R_{SS} Otherwise, please define it.
Introduction.
“Several studies have reported a robust negative correlation between SSIs and transmitted power”. It would be of interest to explain why this correlation is negative.

It is unclear what is different about this new app, “5G Scientist Monitor,” compared to the ones you mentioned, i.e., XMobiSense, ElectroSmart, Quanta Monitor, and QualiPoc Android.

Methods.
Measurement Tools.
What about iOS (Apple) phones?
Figure 1. A) Three broadband E-field sensors. Aren’t they 2? Please, clarify.
Table 2. Why only the right hand?
Have you planned to consider exposure when using headphones?

Data analysis and modeling.
Why normalization is done for f_0 = 1800 MHz?
“These aggregates were computed for each unique combination of location, phone, provider, and scenario (n=795 in NL and n=325 in FR) by taking the arithmetic mean of the app SSIs, and of the recorded ExpoM-RF4 and probe electric field strengths during the interval”. You have averaged all your data without considering the location. Nevertheless, in Figure 6 you show data also as a function of the location. Could you also show the n relatives to the different locations?
Table 3. Check the spelling of ‘receive power’ in Implications, Technical conversion function

Results.
Location seems to play a significant role in exposure levels when measured with the app compared to the ExpoM-RF4 measurements (Fig.6). Could you comment a bit more on that?

Moreover, it would have been interesting to see a similar data representation in Figure 5 as the one shown in Figure 6. It would also be helpful to include a legend in Figure 6 to clarify the color coding for each location.

Figure 7 would be clearer with a legend explaining the name of the points used for the regression.

“Additionally, the results of the far-field conversion function for 5G-NR showed that NR-ssRSRP was not a significant predictor of neither active-band nor NR exposure, which was always from a TDD band (Figure S10 in Extended Data28)”. Could you explain why?

Figure 8. Please, provide more information about it in the caption. Please, justify the choice of 4G, native call, WAvoice, etc.

Discussion.
“Our study provides initial findings regarding the complex relationship between RF-EMF exposure and SSIs within the framework of 5G-NR technology.”. However, If I have well understood, most of the data that you show are relative to 4G. Could you please comment on that?

Is the rationale for, and objectives of, the study clearly described?

Yes

Is the study design appropriate for the research question?

Yes

Are sufficient details of the methods provided to allow replication by others?

Yes

Are the datasets clearly presented in a useable and accessible format?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Therapeutic bioelectromagnetics, experimental electromagnetic dosimetry

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 27 Mar 2025

Nekane Sandoval-Diez

Comment: The authors outline the development and evaluation of the "5G Scientist Monitor," an open-access mobile app created within the frame of the EU project ETAIN to estimate radiofrequency electromagnetic field (RF-EMF) exposure from smartphones using

different signal strength indicators (SSIs). The paper is very interesting and well-written. Please, find below a few comments. ***Answer:*** The authors would like to thank the reviewer for taking the time to read our manuscript and providing insightful comments and constructive feedback. Below, we address each point raised:

- Abstract.
  - ***Comment***: RSSI. If it is the R coefficient of the linear regression I would express it as RSS Otherwise, please define it. ***Answer***: Thank you for the suggestion. RSSI refers to the Received Signal Strength Indicator, and the acronym has now been defined in the abstract.
- Introduction
  - ***Comment:*** "Several studies have reported a robust negative correlation between SSIs and transmitted power". It would be of interest to explain why this correlation is negative. ***Answer:*** We appreciate the comment and have added an explanation clarifying why this correlation is negative.
  - ***Comment:*** It is unclear what is different about this new app, "5G Scientist Monitor," compared to the ones you mentioned, i.e., XMobiSense, ElectroSmart, Quanta Monitor, and QualiPoc Android. ***Answer***: Thanks for the observation, we have added a sentence to make this clearer. The ETAIN 5G Scientist app, like the other mentioned apps, collects SSI data. However, it stands out by adopting a citizen science approach, involving both citizens and experts in its design to better address public needs and enhance engagement. Additionally, the ETAIN 5G Scientist app implements a reproducible and documented framework for estimating RF-EMF exposure from app-collected data, which distinguishes it from other apps that often provide limited details about their calculation processes.
- Methods. Measurement tools
  - ***Comment:*** What about iOS (Apple) phones? ***Answer***: Developing the app for iOS posed significant challenges due to Apple's stricter access policies regarding internal phone parameters. These limitations made it complicated to integrate the app into the Apple ecosystem. As a result, the app is only available on Android.
  - ***Comment:*** Figure 1. A) Three broadband E-field sensors. Aren't they 2? Please, clarify. ***Answer:*** Thank you for spotting the typo; it has been corrected in the figure.
  - ***Comment:*** Table 2. Why only the right hand? ***Answer***: The right hand was specified to standardize the measurement protocol and minimize inter-operator variability.
  - ***Comment:*** Have you planned to consider exposure when using headphones? ***Answer***: Our focus in this study was on RF-EMF exposure from mobile phone use and mobile telecommunication technologies. While we did not include exposure from peripherals or other wireless technologies, we recognize their relevance and consider it a topic for future research.
- Data analysis and modelling
  - ***Comment:*** Why normalization is done for f0 = 1800 MHz? ***Answer***: Normalisation was performed for f0 = 1800 MHz it is centrally located within the frequency bands used in mobile networks. This choice has now been clarified in the text.

- ***Comment:*** These aggregates were computed for each unique combination of location, phone, provider, and scenario (n=795 in NL and n=325 in FR) by taking the arithmetic mean of the app SSIs, and of the recorded ExpoM-RF4 and probe electric field strengths during the interval". You have averaged all your data without considering the location. Nevertheless, in Figure 6 you show data also as a function of the location. Could you also show the n relatives to the different locations? ***Answer***: Thank you for the suggestion. We have added the sample sizes (n) for the locations and expanded the explanation of the aggregation process used for the map conversion function shown in Figure 6.
- ***Comment:*** Table 3. Check the spelling of 'receive power' in Implications, Technical conversion function. ***Answer***: Thank you for noting the typo. The typo has been corrected in the table.

- Results
  - ***Comment:*** Location seems to play a significant role in exposure levels when measured with the app compared to the ExpoM-RF4 measurements (Fig.6). Could you comment a bit more on that? ***Answer***: Thank you for your comment, we have elaborated more on this in the results section. The ExpoM-RF4 measures the combined exposure from all providers, while the app captures provider-specific signals. Geographic variability in base station density and provider distribution accounts for the observed differences.
  - ***Comment:*** Moreover, it would have been interesting to see a similar data representation in Figure 5 as the one shown in Figure 6. It would also be helpful to include a legend in Figure 6 to clarify the colour coding for each location. ***Answer***: Thank you for your suggestion. We believe that adding a colour code for each location in Figure 5 would not enhance the interpretation of the results. Figure 5 presents band-specific exposure levels correlated with the SSI from the serving cell. In this context, location primarily influences the frequency band used for communication, as lower frequencies are typically employed in areas with lower network coverage. Therefore, we opted to use colour codes to represent the frequency bands in Figure 5.
  - ***Comment:*** Figure 7 would be clearer with a legend explaining the name of the points used for the regression. ***Answer:*** To improve clarity, we opted to change Figure 7 to include a colour code representing the level of urbanisation and type of microenvironment for each location.
  - ***Comment:*** "Additionally, the results of the far-field conversion function for 5G-NR showed that NR-ssRSRP was not a significant predictor of neither active-band nor NR exposure, which was always from a TDD band (Figure S10 in Extended Data28)". Could you explain why? ***Answer:*** We elaborated an explanation for this in the discussion section.
  - ***Comment:*** Figure 8. Please, provide more information about it in the caption. Please, justify the choice of 4G, native call, WAvoice, etc. ***Answer:*** We have added a detailed explanation of the reasons for stratification in the methods section and have expanded the caption of Figure 8 to provide further context.
- Discussion
  - ***Comment:*** "Our study provides initial findings regarding the complex relationship between RF-EMF exposure and SSIs within the framework of 5G-NR technology.". However, If I have well understood, most of the data that you

show are relative to 4G. Could you please comment on that? ***Answer:*** Yes, most of the data in our study is based on 4G-LTE technology, as 5G-NR had not yet been deployed in the Netherlands at the time of data collection. However, we conducted a preliminary analysis of the available 5G-NR data from Lyon (F) to identify opportunities for future research.

Competing Interests: No competing interests were disclosed.