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Review article

A comprehensive review of 5G NR RF-EMF exposure assessment technologies: fundamentals, advancements, challenges, niches, and implications

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ABSTRACT

This review offers a detailed examination of the current landscape of radio frequency (RF) electromagnetic field (EMF) assessment tools, ranging from spectrum analyzers and broadband field meters to area monitors and custom-built devices. The discussion encompasses both standardized and non-standardized measurement protocols, shedding light on the various methods employed in this domain. Furthermore, the review highlights the prevalent use of mobile apps for characterizing 5G NR radio network data. A growing need for low-cost measurement devices is observed, commonly referred to as “sensors” or “sensor nodes”, that are capable of enduring diverse environmental conditions. These sensors play a crucial role in both microenvironmental surveys and individual exposures, enabling stationary, mobile, and personal exposure assessments based on body-worn sensors, across wider geographical areas. This review revealed a notable need for cost-effective and long-lasting sensors, whether for individual exposure assessments, mobile (vehicle-integrated) measurements, or incorporation into distributed sensor networks. However, there is a lack of comprehensive information on existing custom-developed RF-EMF measurement tools, especially in terms of measuring uncertainty. Additionally, there is a need for real-time, fast-sampling solutions to understand the highly irregular temporal variations EMF distribution in next-generation networks. Given the diversity of tools and methods, a comprehensive comparison is crucial to determine the necessary statistical tools for aggregating the available measurement data.

Contents

1. Introduction 2
2. Methods 3
3. Fundamentals of EMF measurements 3
   3.1. Exposure guidelines 3
   3.2. Standardized measurement protocols 4
   3.3. Non-standardized measurement protocols in exposure assessment studies 5
   3.4. Specifications of measurement devices, calibration, and uncertainty assessment 6
4. State-of-the-art RF-EMF measurement instruments 7
   4.1. High-end commercial instruments 7
      4.1.1. Frequency scanning and selective instruments employed in measurements of RF-EMF exposure 7
      4.1.2. Broadband field meters 7
      4.1.3. Area monitors 7
      4.1.4. Commercial exposimeters 7

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4.2. Custom-developed instrument and sensors 8
4.2.1. Laboratory-designed broadband probes 8
4.2.2. SDR-based sensor nodes 8
4.2.3. Hardware-based compact measurement nodes 9
4.2.4. Lab-built exposimeters 10
4.2.5. Cardinal research on human studies 11
5. Mobile phone based tools 11
5.1. Intercomparison and applications 12
5.2. Mobile applications on human studies 13
6. Use cases 13
6.1. Stationary measurements 13
6.2. On-body measurements 13
6.3. Vehicle-mounted measurements 14
6.4. Distributed network measurements 14
6.5. Measurement uncertainty 14
6.6. Discussions regarding use in 5G exposure assessment 14
7. Conclusions 15
CRediT authorship contribution statement 15
Declaration of competing interest 16
Data availability 16
Acknowledgments 16
Appendix. Abbreviations 16
References 16

1. Introduction

The rapid evolution of wireless communication technologies has revolutionized the way we connect, communicate, and access information. The introduction of fifth-generation (5G) New Radio (NR) networks in late 2018 promises unprecedented speed, lower latency, and enhanced connectivity (the ability to handle a larger number of simultaneous connected devices). One of the major innovations brought by 5G NR technology is the utilization of active antenna systems, such as Massive Multiple-Input Multiple-Output (MaMIMO) antennas, where multiple signal propagation paths (i.e., spatial multiplexing) can be used to maximize the data transfer rate (Lin et al., 2019). In MaMIMO a multitude of antenna elements, potentially numbering in the hundreds (or even thousands), can be employed to focus and adjust the transmission beam, aiming to optimize the signal reception at the receiver device. Applications such as the internet of things (IoT), and autonomous vehicles and robotics need 5G because of the low latency and high throughput. However, these technological advancements have also raised concerns about potential health risks associated with possible increased exposure to radio frequency electromagnetic fields (RF-EMF). In fact, the usage of MaMIMO antennas introduces a spatiotemporal variability of the radiated field distribution which depends on the specific use case and scenario (Shikhantsov et al., 2023) and is for this reason difficult to predict a priori. As the deployment of 5G NR networks continues to expand globally, comprehending and monitoring EMF exposure levels have become crucial in ensuring public safety and addressing potential exposure-effect relations.

The International Commission on Non-Ionizing Radiation protection (ICNIRP) published exposure limits based on scientifically proven causal effects (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 2020), mostly based on short term exposure, such as the perception of surface electric charge, direct stimulation of nerve and muscle tissue, and the induction of retinal phosphenes. Studies focusing on exposures below established limits or utilizing alternative metrics necessitate epidemiological research to establish meaningful relationships between exposure and adverse health effects. In case of medically unexplained physical symptoms or (self-declared) electrosensitivity or rare diseases epidemiological approaches concurrently monitoring exposure and bioparameters at the individual level is a necessary addition. In these studies, the subjects act as their own controls, In contrast to the classic group-level comparisons, as is the case in ecological momentary assessment e.g. Bogers et al. (2018), Bolte et al. (2019), Van Wel et al. (2017).

The evaluation of RF-EMF personal exposure measurements in human epidemiological studies has posed a considerable challenge due to the need to accurately measure individual exposures to reduce the likelihood of exposure misjudgment (Bhatt et al., 2015; Bolte, 2016). Epidemiological studies have frequently relied on subjective and less precise methods for assessing exposure, both in terms of estimating exposure levels and categorizing study participants as either exposed or unexposed populations (Brzozek et al., 2019). The choice of exposure assessment tool(s) and the methodology employed in human epidemiological studies directly impact their reliability. Consequently, in recent years there has been progress in developing and implementing (sensitive) instruments to characterize the realistic EMF exposure levels.

Both, the assessment of the exposure and of the health status, in epidemiological studies should be accurate and objectively measured. In case the individual exposure is not accurately assessed by personal measurement devices, so-called exposimeters, but predicted as is the case in using proxies as the distance to a transmitter, or a single measurement (Frei et al., 2009), this may lead to a misclassification of the exposure level (Bhatt et al., 2015; Bolte, 2016). This is often an underestimation, therefore leading to a weaker correlation, if any, between exposure and effect. If the health effect is not objectively based on sensor measurements of bioparameters such as heart rate, respiratory frequency etc., but by a questionnaire with a likert scale on perception of pain or mental status, recall bias may occur and the reporting of the intensity will be very subjective, again leading to a decrease in the correlation.

At the same time, urban areas are progressively embracing the implementation of intelligent sensor networks to provide all-encompassing surveillance of diverse facets of city life, including variables like noise levels, air quality, temperature and EMF exposure (Díez et al., 2017). These sensor networks are defined by their cost-efficiency and ease of use, rendering them accessible instruments for monitoring the urban environment. They are designed to guarantee uninterrupted wireless connectivity and seamless integration with the IoT (Li et al., 2018; Wang et al., 2018). A significant benefit of these geographically distributed sensor networks lies in their capacity to provide extensive and continuous data on RF-EMF exposure across multiple locations. Governments and regulatory authorities can leverage on these networks to assess and monitor RF-EMF levels over extended periods, thus facilitating a more nuanced understanding of electromagnetic field exposure in urban settings.

In recent years, several European countries have embraced the establishment of stationary RF-EMF exposure monitoring networks. By leveraging the capabilities of low-cost, user-friendly sensors and RF-EMF-based wireless communication, cities are taking significant strides toward creating smarter and more informed urban landscapes. Notable examples include Spain, Portugal, Greece, Serbia, Italy, Romania, France, Hungary and Belgium (Díez et al., 2017; Oliveira et al., 2007; Manassas et al., 2012; Troisi et al., 2008; Apostolidis et al., 2022; Aerts et al., 2022; Djurić et al., 2022), where initiatives have been undertaken to deploy sensor networks for the systematic measurement of ambient RF-EMF exposure levels. These networks contribute to enhance our awareness of existing RF-EMF exposures and also serve as valuable resources for policymakers and researchers to make informed decisions regarding human and environmental protection.

Over the past decade, several studies have been published assessing environmental and personal EMF exposure globally (mostly in Europe) for human epidemiological studies (Chiaramello et al., 2019; Sagar et al., 2017; Ramírez-Vázquez et al., 2023). Although a few studies have provided reviews on personal RF-EMF exposure measurements tools (Bhatt et al., 2015; Bolte, 2016; Bhatt et al., 2022), they are particularly related to previous (i.e.non-5G) technologies. The latest systematic review (Sagar et al., 2018) on measurement studies of RF-EMF exposure shows that only a few (5 out of 56) measurement studies were conducted in developing countries. This indicates the underutilization of RF-EMF sensors and the inadequacy of exposure monitoring programs in developing countries despite the similar trend of telecommunication technology deployment. One of the reasons behind this could be that RF-EMF exposure assessment tools are generally expensive and therefore are often beyond the reach of developing countries. Therefore, there is a need of developing relatively low-cost RF-EMF sensors that can be accessed and deployed more widely.

A rapid deployment of 5G NR technology worldwide and its ramifications in developing 5G-specific assessment tools highlights the need for reviewing 5G NR exposure assessment and monitoring tools reflecting the current landscape of 5G NR network deployment and associated exposure monitoring programs in different contexts. Therefore, a comprehensive review on 5G NR monitoring tools not only supports the field of RF-EMF exposure assessment for human protection but also for emerging need of environmental protection (Karipidis et al., 2023). The purpose of this review is to undertake an in-depth examination of 5G NR specific RF-EMF exposure sensors, highlighting on the advancements, challenges, niches and implications associated with them.

This study is dedicated to a comprehensive examination of the instruments featured in the scientific literature for the measurement of 5G RF-EMF exposure. It starts with the basics of exposure guidelines and the standardized and non-standardized measurement protocols, followed by measurement device specifications and the fundamentals of calibration and measurement uncertainty. Then it delves into detailed descriptions of these instruments and the passive components integrated into their test setups, categorizing them into two main groups: commercially available devices and custom-built devices employed in and outside laboratory settings. The document also provides a clear explanation of their operational mechanisms. Additionally, a special attention is given to mobile phone applications assessing RF-EMF exposure. Furthermore, cardinal research on human studies using EMF sensing technologies is presented.

Finally, it is worth noting that various types of EMF exposure measurement devices serve distinct purposes, each aligned with specific objectives. Hence, this review offers in-depth discussions on different scenarios from environmental exposure assessment to check for legal compliance, to microenvironmental exposure levels, to individual exposure effect assessment in epidemiological studies, and the EMF exposure instruments required. It provides insights into the essential performance parameters that guide the development of measurement equipment tailored specifically for assessing 5G exposure. For space requirements 5G NR measurement methods are not included in this review, the interested reader is invited to review (Fellan and Schotten, 2022) for more information on this topic.

2. Methods

To systematically compile relevant literature and perform an effective synthesis, an extensive search of scientific literature was conducted for peer-reviewed scientific publications. This survey encompassed a comprehensive search across prominent academic databases, including Scopus, Google Scholar, Web of Science, and Medline. The focus of this survey was primarily on the last decade, ensuring that the collected literature was not only pertinent but also reflective of the most recent advancements and insights in the field. The methodology involved careful screening of articles, abstracts, and keywords to select studies aligning with the research objectives. Additionally, the reference lists within the chosen works were further scrutinized including cross reference check to broaden the scope of the literature review.

A selection of the following keywords has been employed, to identify the main contributions over the years 2013–2023, for the literature survey:

- Frequency identification: Frequency Range 1, FR1, Frequency Range 2, FR2, millimet* wave*, millimet* frequenc*, mmwave, mm-wave
- Telecommunication system identification: Fifth generation, 5G, New Radio, 5G NR
- Field definition #1: Exposure, human exposure, personal exposure
- Field definition #2: Measure*, sens*, instrument, device, equipment

In addition, we also searched for any grey literature, such as reports, vendors information sheet, etc. to get most up-to-date information on the tools.

3. Fundamentals of EMF measurements

To establish the groundwork for our discussion on the most recent developments in EMF measurement equipment, it is imperative to begin by introducing the fundamental aspects of EMF measurements, which play a critical role in this review. We begin with exposure guidelines and measurement protocols followed by the specifications of measurement devices and explain which specifications are considered.

3.1. Exposure guidelines

The exposure guidelines and standards issued by ICNIRP (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 2020) and the International Committee on Electromagnetic Safety of the Institution of Electrical and Electronic Engineers (ICES-IEEE) (IEEE-ICES, 2019) are determined to protect against potential adverse health effects which have been scientifically proven, established through evaluations of pertinent scientific literature. These guidelines encompass fundamental constraints on EMF exposure of the human body (or parts of), which are articulated in quantities associated with potential adverse short-term health effects, such as rise in temperature. In the case of high-frequency electromagnetic fields (100 kHz–300 GHz), the goal of these basic restrictions (in terms of the specific absorption rate or SAR) is to limit the temperature increase to 1 °C for the whole body, and to 5 °C and 2 °C, for the limbs and head, respectively (local exposure) (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 2020).

To ascertain protection of exposed people, an additional safety or reduction factor is applied, for which a differentiation was made

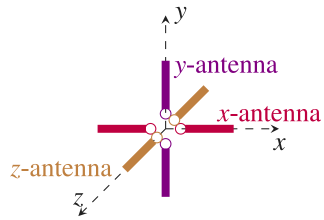


Fig. 1. Triaxial dipole antenna example.

between exposure of the general public (factor of 50) and exposure in occupational settings (factor of 10) in which the exposed persons are supposed to be aware of the potential risks. As SAR (W/kg) can only be directly measured in the body, the basic restrictions were translated into so-called reference levels (root-mean-square (RMS) values) for the electric field strength, E (V/m), magnetic field strength, H (A/m) or for the plane wave power density, S (W/m^2), which are measured outside the body. The translation is such that as long as the reference level is not exceeded, the basic restriction remains satisfied. The SAR is a time-averaged quantity and when examining the entire body, this average is taken over a period of 30 min. However, for localized exposure (e.g., 10 g of tissue), the averaging time is reduced to 6 min or less. For local exposure within the 6–300 GHz frequency range, the basic restriction is $100\,\mathrm{W/m^2}$ for workers and $20\,\mathrm{W/m^2}$ for the general public, averaged over a $4\,\mathrm{cm^2}$ area.

When conducting EMF measurements for compliance assessment (e.g., comparing to ICNIRP reference levels or other legal limits), it is crucial to consider the distance between the measurement setup and the radiation source. IEC 62232 (IEC 62232:2022, 2022) addresses the evaluation of RF field strength in the far-field region (Balanis, 2016). However, when exposure occurs at shorter distances (near field), it is necessary to measure both electric and magnetic field levels or, alternatively, revert to the basic restrictions.

The RF power detectors which are used in measurement instruments produce a DC output that is proportional to the RMS value of the signal which then sampled with an analog-to-digital converter (ADC) and is converted into a power level (dBm) using a lookup table within a standard microcontroller/processor. This power level can subsequently be converted into an electric field using the antenna factor. Initially, the power density needs to be computed using the following formula:

$$S = \frac{4\pi P_r}{\lambda^2 G} \tag{1}$$

in which P_r is the received power (W), λ is the wavelength in free space, and G is the gain of the antenna. Then, the magnitude of electric field intensity can be calculated by:

$$E = \sqrt{S\eta_0} \tag{2}$$

where $\eta_0 = 120\pi$ is the free space impedance (Ω).

Moreover, it is assumed that the external field is optimally linked to the individual. This entails that the assessment of exposure takes into account all potential polarizations and propagation directions. To accomplish this, the RMS value of the electric or magnetic field strength are measured using three co-located orthogonal sensors or antenna elements as illustrated in Fig. 1.

3.2. Standardized measurement protocols

Government agencies typically oversee the regulation of EMF generated by services operating within specific frequency bands. For instance, within the EU, this oversight often involves assessing compliance with the ICNIRP basic exposure restrictions. However, stricter limits exist in various European countries or regions, initially established by the 1999/519/EG Council Recommendation on limiting public exposure to electromagnetic fields (0 Hz to 300 GHz) (Publications Office of the European Union, 1999), and the Directive 2013/35/EU (workers directive) (Publications Office of the European Union, 2013), both derived from the ICNIRP 1998 guidelines (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 1998). A practical guide for EMF measurements to assess human exposure are summed in International Telecommunication Union - Radiocommunication Sector (ITU-R) (2019).

Although the ICNIRP 2020 guidelines (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 2020) were released some time ago, they have yet to be officially adopted by the European Council (EC). Nevertheless, the Scientific Committee on Health, Environmental, and Emerging Risks (SCHEER) has recommended EC adoption, and many agencies already implement these guidelines (Scientific Committee on Health, Environmental, and Emerging Risks (SCHEER), 2023).

Qualified personnel perform RF-EMF measurements using European harmonized standards, particularly EN 62232 (IEC 62232:2022, 2022) and EN 50401 (EN 50401, 2017). Isotropic measurements must be conducted with calibrated instruments in accordance with EN 50383 (EN 50383, 2023).

In general, standardized EMF measurements are conducted at specific fixed locations and at a particular point in time with either broadband or frequency-selective equipment.

Broadband measurements involve the integration of all emissions across a wide spectrum, e.g., spanning from 100 kHz to 6 GHz. This spectrum encompasses signals from various sources, such as broadcast stations (AM, FM, T-DAB, DVB-T) and mobile phone base stations (2G, 3G, 4G, 5G). It is necessary to extend the frequency range for broadband measurements because of the forthcoming deployment of 5G in the millimeter wave spectrum (FR2 bands, i.e., between 24.25 GHz and 71.00 GHz).

Frequency-selective measurements are conducted at specific bands, such as those associated with a particular technology or operator. These measurements serve as a supplementary procedure when broadband measurements exceed a predefined threshold (e.g. $0.1\,\mathrm{W/m^2}$) (IEC 62232:2022, 2022). This measurement type enables the collection of incident power density within a designated frequency range. Using the measured value of specific, reference signals per technology, the maximum potential electromagnetic field at a particular location can be calculated based on extrapolation (IEC 62232:2022, 2022). Frequency-selective measurements are performed at specific, fixed locations and at a particular moment in time.

The RF-EMF levels determined by these measurements represent a snapshot, influenced increasingly by the behavior of the (cellular) network, such as the total amount of data traffic, especially in the latest- and future generations of telecommunications networks. Therefore, an extrapolation can be carried out based on a frequency-selective measurement to make a prediction of the maximum possible electromagnetic field.

In order to assess the average incident power density to which the body is exposed, ICNIRP 2020 (International Commission on Non-Ionizing Radiation Protection (ICNIRP), 2020) guidelines recommend a 30-minute measurement duration. Nevertheless, from a practical standpoint, it is viable to limit the measurement duration to 6 min, unless the measured exposure exceeds a certain threshold (e.g., 5% of the value specified in the ICNIRP guidelines (Anon, 2021a)).

In order to perform these standardized (compliance) EMF measurements, the following considerations can be taken into account (Anon, 2021b):

- Ensure that there are no nearby transmissions originating from your own devices (e.g., switch mobile phones off or put them in to airplane mode).
- Ensure that the measurements are performed in the far field from the emission sources.
- Place the measurement device on a non-conducting (e.g. wooden) tripod at a height of 150 cm above street level.

- The measured field value should represent the ‘undisturbed’ field, free from any human body interference.
- Avoid large conducting objects or surfaces in close proximity to the measurement device (maintain a distance greater than 0.5 m).
- Be aware of temporal variations in field strength related to actual traffic conditions.
- The measurement device should employ an RMS detector and record data.
- Empirically identify the local maximum instantaneous RMS exposure value by conducting a quick scan in the area of interest (worst-case exposure) using a broadband probe.
- For frequency-selective measurements, select a measurement bandwidth that is wider than the signal(s) of interest.
- Compare the measurement results with limit values, expressed as a percentage of exposure relative to the value of ICNIRP guidelines.

A crucial part of compliance assessment is the measurement uncertainty. The estimation of EMF measurement uncertainty is carried out following the procedures outlined in EN 50383 (EN 50383, 2023) and EN 50413 (EN 50413, 2023). The expanded uncertainty must not exceed 4 dB at a 95% confidence interval (using an expansion factor of 1.96) for frequencies up to 6 GHz. The Root Sum of the Squares (RSS) method is employed for calculating uncertainty, considering sources such as calibration (antenna, cable, receiver), mismatch, and repeatability. It is worth noting that for frequencies above 6 GHz, this information needs to be updated.

3.3. Non-standardized measurement protocols in exposure assessment studies

Besides compliance testing, measuring RF-EMF serves various other objectives, including but not limited to: estimating realistic exposure levels (Liorni et al., 2020), validating numerical models (Beekhuizen et al., 2013), comparing average exposure levels across different geographical regions (Velghe et al., 2019), tracking the evolution of exposure levels over time (Velghe et al., 2019), creating exposure heat maps for specific areas (Aerts et al., 2018), and evaluating exposure levels among specific population segments (Eeftens et al., 2018).

For many of these purposes, the measurement techniques and materials typically employed for compliance testing are not the most suitable choices. This can be attributed to a variety of factors, including the time required, the cost of specialized measurement equipment, and their physical size. In many cases, measurements need to be conducted at multiple locations, individuals being tested must carry measuring devices without significant disruption to their daily routines, or measurements have to be performed continuously for extended periods in locations where delicate equipment could be at risk of damage.

Hence, to address these challenges, alternative devices have been developed alongside high-end commercial instruments. These alternative devices can be categorized into three main groups: wearables, smartphone applications, and more affordable sensor nodes.

These devices, along with the measurement protocols they employ, tend to introduce a greater level of measurement uncertainty when contrasted with high-end bench-top testing equipment (Bolte, 2016). Nonetheless, their primary purpose is to gather extensive data, and through the application of statistical techniques, meaningful and scientifically relevant conclusions can be derived.

Below, the most commonly used non-standardized measurement protocols are elaborated.

Microenvironmental studies:

The objective of microenvironmental studies is to assess the electric field strength or exposure by studying multiple locations of a similar type (Thielens et al., 2018; Röösli et al., 2010; Bhatt et al., 2016a,b; Vermeeren et al., 2013; Sagar et al., 2018; Thielens et al., 2018; Jalilian et al., 2019). These types of locations or microenvironments (MEs) distinguished by the activities taking place within them, describe the typical sequence of locations people may spend time in. These may be aggregated in at home, work, elsewhere inside, shopping, outdoor. And within these main categories, depending on the number of samples, subsets can be defined, for instance for transport: waiting at railway station, waiting at bus stop. Other important levels defining the exposure level are time of day (night, morning, afternoon, evening, rush hour), season and type of area (rural, suburban, urban) (Bolte and Eikelboom, 2012; Frei et al., 2009).

The study establishes a route through these MEs and conducts a series of repetitive measurements, possibly divided into specific time intervals, using wearable devices.

Microenvironmental measurements can be conducted using various modes of transportation, such as drones, cars, bicycles, and more. The devices employed in these surveys are wearable, capable of measuring across multiple frequency bands, and operate at a rapid rate, typically recording data every 3 s across all frequency bands. Their utilization is primarily confined to assessing environmental exposure, which pertains to exposure outside of the user’s control.

Presently, microenvironmental measurements are exclusively conducted in non-user scenarios, and the recorded exposure is categorized as environmental exposure. However, a protocol for microenvironmental measurements in 5G NR networks has been proposed in Velghe et al. (2021), encompassing both environmental and self-induced exposure. To obtain a representative measurement of exposure, a minimum of 15 min of data acquisition is required (Urbinello et al., 2014).

Survey studies:

The objective of a survey study is to evaluate individual exposures specific to distinct population groups (Eeftens et al., 2018). These groups are typically characterized by factors like age, residential location, and occupation type. From each subset, a select number of participants are chosen and provided with a portable and/or wearable measuring device. Participants are required to carry the measurement device with them for several days and maintain a diary of their activities (Van Wel et al., 2017). Additionally, the measurement device often records GPS data (Van Wel et al., 2017). Key requirements include the random selection of participants who are representative of their respective population subsets and ensuring that the participant sample size is sufficiently large (Eeftens et al., 2018).

Distributed sensor networks:

Distributed networks consisting of multiple sensor nodes (typically ranging from tens to hundreds of nodes) allow us to monitor EMF over a significant geographic area, often covering a section of a city (Aerts et al., 2022; Iakovidis et al., 2022; Gotsis et al., 2008; Manassas et al., 2012; Anon, 2024e; Oliveira et al., 2007; Rowley and Joyner, 2016; Díez et al., 2017; Aerts et al., 2018; Djurić et al., 2022). These networks have the potential for open data and dashboard applications.

These nodes can be positioned in stationary locations, including both indoor and outdoor public spaces (forming a fixed network), or they can be mounted on various vehicles like postal service cars (Aerts et al., 2022) (constituting a mobile network). Sensor networks are designed to accumulate exposure data over extended period of time, ranging from weeks to years.

Through these networks, it becomes feasible to assess the temporal progression of exposure levels, whether in specific frequency bands or across the entire spectrum (i.e., broadband). This facilitates the creation of spatiotemporal exposure heat maps. Given the substantial number of required devices and their susceptibility to potential damage when located in public areas, there is a necessity to develop these nodes cost-effectively.

Spot measurements:

Spot measurements (Joseph et al., 2012a; Aerts et al., 2013b; Joseph et al., 2012b) are versatile, suitable for both compliance testing as detailed in Section 3.2, and non-standardized measurements. For instance

Table 1
Parameters which influence the bias and uncertainty of the recorded EMF response.

Antenna(s)	Number of Antennas Type (monopole, dipole, patch, or other) Radiation pattern Polarization Frequency band(s) Antenna gain [dB] Antenna aperture [m^2]
Detector	Amplification level Filter Type (diode, logarithmic, true RMS, or other) Dynamic range [dB] - Sensitivity (Minimum level) [dBm, V/m, or W/m^2] - Maximum level [dBm, V/m, W/m^2]
ADC	Sampling time [s] Resolution - Number of bits - Unit [dBm, V/m, W/m^2]
Power supply	mains-powered, solar-powered, battery-powered (autonomy [h]), or other
Output	Quantity (voltage, power, power density, or electric-field strength) Aggregation time [s] Aggregated parameter (minimum, maximum, arithmetic average, geometric average, or other) Logging interval [s]

for standardized measurements, they prove invaluable in validating the computational tools employed to evaluate the suitability of base station (BS) placement near sensitive locations like schools or residential areas (Ramírez-Vázquez et al., 2020). Spot measurements can also find application in fundamental scientific research, such as the advancement of BS technology or the formulation of new measurement protocols (Aerts et al., 2019). In the latter scenario, these measurements may involve the use of high-end laboratory equipment, making the process more labor-intensive, as will be discussed in Section 4. In addition, spot measurements can also be used to validate sensor measurements or ME measurements.

However, spot measurements are not suitable for determining one's personal exposure, as they do not move through space meeting all kinds of object- and person-shadow zones or focal zones. Even exposure measured within a position in a room may be different at another position in that room (Frei et al., 2010).

3.4. Specifications of measurement devices, calibration, and uncertainty assessment

For EMF measurements, the choice of device varies depending on the specific assessment goals and the corresponding measurement protocols (a comprehensive overview of EMF measurement device types is provided in Section 4). However, regardless of the method or equipment used, it is essential for the completeness and credibility of reported measurements to include a description of the associated measurement uncertainty.

Best practices entail the identification of various sources of uncertainty that contribute to the overall uncertainty in measurements. This collection of individual sources and their potential correlations is referred to as an "uncertainty budget" (Stratakis et al., 2009). This becomes particularly significant when measured values approach the reference levels and exposure limits established by international organizations like ICNIRP, standardization bodies such as the International Electrotechnical Commission (IEC) and the European Committee for Electrotechnical Standardization (CENELEC), or national/regional legislation.

The uncertainty budget of the measurements includes systematic errors, biases, and random errors (uncertainty) associated with the measurement device, setup, and measurement circumstances. The details of the measurement device under consideration are provided in Table 1.

Various factors contribute to systematic errors. In order to be able to compare measurements under different circumstances, between different measurement setups or devices systematic errors can be partially corrected by whitebox models that describe the dependence of the measurements on environmental variables or frequency. For instance temperature and humidity influence most measurements according to a well known response curve. While commercial devices come with calibration certificates, ensuring that correction factors have been established and applied, a study by Bolte et al. (2011) notes that these certificates are issued per device type rather than per individual device, as they ideally should be.

The persisting random effects continue to introduce measurement uncertainties (see Section 6.5). These uncertainties should also be assessed during the calibration process and documented in the calibration certificates. These include uncertainties stemming from modulation errors, resolution, anisotropy, linearity, and frequency response (IEC 62232:2022, 2022; Anon, 2013).

In addition to the equipment-related biases mentioned above, the overall uncertainty budget also encompasses uncertainties associated with unknown (not whitebox) measurement conditions, including environmental factors such as scattering, reflections, the influence of nearby objects and individuals, and the measurement method itself.

Other sources of random errors such as interoperator variability, intraoperator variability, rounding errors, etc. should be statistically be taken into account and formulated as uncertainties. Furthermore, post-processing factors like spatiotemporal averaging as well as the sampling interval and duration, upper and lower threshold, and noise floor, and temporal drift should be taken into consideration.

It is worth emphasizing that all these various sources of uncertainty contribute to the overall combined uncertainty. The purpose of combining uncertainties is to calculate the total magnitude of uncertainty by considering a set of independent uncertainty components. This process is commonly referred to as 'Summation in Quadrature' or 'Root Sum of the Squares' (Dietrich, 1991).

Subsequently, the combined uncertainty is expanded (i.e., multiplied by a factor greater than 1) to obtain a desired coverage factor, which dictates the level of confidence associated with data points within a specific standard deviation range. For instance, if a coverage factor of 1 is assumed, it indicates a confidence level that 68% of data points fall within one standard deviation. On the other hand, a coverage factor of 2 implies a confidence level that 95% of the data points would fall within a range of two standard deviations (Anon, 2024c).

4. State-of-the-art RF-EMF measurement instruments

A range of instrument categories suitable for RF-EMF exposure assessments are presented, as employed in measurement campaigns documented in peer-reviewed publications. These categories encompass a variety of instruments, ranging from advanced high-end laboratory equipment to lab-developed standalone devices and sensors. Generally, a brief overview of the operational mode of certain equipment type is provided, highlighting different configurations. Subsequently, we present tables detailing the critical performance parameters for different instrument categories, drawing from peer-reviewed publications. Additionally, a comparative study for certain lab-build devices is presented.

4.1. High-end commercial instruments

4.1.1. Frequency scanning and selective instruments employed in measurements of RF-EMF exposure

The primary category of instruments employed for signal detection, demodulation, and field level measurement across a broad frequency spectrum and bandwidths is known as spectrum/signal analyzers (SAs). SAs utilize a heterodyne receiver architecture, enabling them to measure the magnitude of an input signal across the entire frequency range of the instrument.

SAs provide best-in-class performance enabling frequency sweeping coverage up to 85 GHz, a sensitivity level, displayed average noise level (DANL), exceeding −160 dBm/Hz and provide analysis bandwidths larger then 8 GHz (Anon, 2023u). While an SA is typically designed by test and measurement equipment manufacturers as a versatile laboratory benchtop instrument, vendors often integrate a similar RF front-end and Digital Signal Processor (DSP) into specialized units which can be used for RF-EMF exposure assessments, known as network scanners (Anon, 2023x; Betta et al., 2023).

The evaluation of RF-EMF exposure for a 5G NR base station using frequency scanning and selective instruments is reported through two methods:

- using a frequency-selective instrument, by measuring the instantaneous electric-field strength sequentially across the channel's bandwidth over a specific duration and calculating the average, resulting in what is known as the time-averaged instantaneous exposure (E_{avg}).
- using a frequency-selective or scanning instrument, by measuring the electric-field strength per resource element of the predominant Synchronization Signal Block (SSB) beam. By assuming the SSBs are transmitted at fixed power, an extrapolation can be made to determine the theoretical maximum exposure (E_{max}) of the base station (IEC 62232:2022, 2022). However, this extrapolation method can also use the electric-field strength per resource element of the downlink traffic beam (PDSCH) directly, which is useful when the gain difference between SSB and traffic beams is not known (Aerts et al., 2019, 2021).

In Deprez et al. (2022), a detailed comparison between these evaluation methods was performed.

4.1.2. Broadband field meters

A portable device for measuring the total electric-field strength or power density across a wide frequency range (ranging from hundreds of kHz up to a hundred GHz) is established by combining a broadband field meter with a triaxial electric field probe. Typically, the field meter display directly indicates the field measurement outcomes, such as the average level E_{avg} over a specific averaging time, and occasionally the minimum and maximum values during that period. Furthermore, advanced broadband field meters, like the Narda FieldMan, incorporate additional functionalities such as a built-in distance meter, compatibility with a smartphone application, and integration with a software platform (Anon, 2023i,h).

Many probes, such as the Narda EF-0691 (Anon, 2023j), employ diode-based sensors characterized by a non-linear response depends on the strength of the measured signal. In this scenario, the sensor acts as a Root-Mean-Square (RMS) detector at lower field levels and transitions to a peak detector at higher field levels (Anon, 2013). In contrast, other probes utilize true Root-Mean-Square (tRMS) thermocouple sensors (Anon, 2023i), which provide a tRMS response. However, this type of detector comes with a trade-off: it reduces sensitivity to 8 V/m (Anon, 2023i), and the dynamic range within the range of 30–40 dB. It is worth noting that, for diode-based probes, the dynamic range within the RMS domain is also typically limited to approximately 40 dB.

The sensitivity of broadband probes varies based on their type and the frequency range they cover. For diode-based probes used in the measurement of FR1 (such as the Narda EF-0691 (Anon, 2023i) and the WaveControl WPF6 (Anon, 2023k), both designed for the 100 kHz to 6 GHz frequency range), the sensitivity is typically at least 0.2 V/m. In older systems with a range of 100 kHz to 3 GHz, the minimum sensitivity was 0.3 V/m (Rowley and Joyner, 2016). For FR2-capable probes designed for very wide frequency ranges (e.g., the Narda EF 9091 (Anon, 2023d), which measures electric-field strength from 100 MHz to 90 GHz), the sensitivity is found to be at least 0.7 V/m.

4.1.3. Area monitors

Closely related to broadband field meters are devices known as "area monitors", such as the Narda AMB series (Anon, 2023g) and the Wave Control MonitEM system (Anon, 2023k). Area monitors are designed for fully autonomous operation and often come equipped with features like solar panels, internal batteries, wireless connectivity, and automatic data transfer. In addition to a processing unit featuring a data logger, they include interchangeable field probes, which can be either broadband or tri/quad-band (to distinguish between mobile telephone services). It is worth mentioning that Narda also offers a selective area monitor capable of monitoring up to 20 individually programmable frequency bands, and MapEM once had the INSITE Box. Furthermore, it is important to note that both Narda and WaveControl offer versions of their area monitors designed for installation on vehicles.

The broadband probes specially designed for area monitors exhibit similarities to those discussed for field meters (for example, you can compare the Narda AMB 8059 with option EP-1B-03 and probe EF-0691 (Anon, 2023g,i). However, the tri/quad-band probes, as well as those used in selective area monitors, demonstrate significantly improved sensitivity, falling within the range of 0.01–0.05 V/m.

4.1.4. Commercial exposimeters

Exposimeters, also known as personal exposure meters (PEMs), are compact wearable devices suitable for use by trained individuals and, in some cases, untrained volunteers (Röösli et al., 2010). Typically, these devices operate as passive objects, requiring no interaction with the body during measurements. Prior to measurement, the device is configured, and data is collected afterward.

PEMs are typically designed to measure within specific radio-frequency bands, which can range in FR1 bands from 1 MHz to 6 GHz, corresponding to various technologies. This approach allows for the segregation of exposure sources from different technologies (e.g., WiFi, 2G–5G) and different sources within these technologies (e.g., uplink (UL) from user devices and downlink (DL) from base stations, which may use different frequency bands). For each dedicated frequency band, PEMs measure the incident electric-field strength or power density. The sampling rate is often customizable by the user, with a typical range of 1 to 3 s.

PEMs are typically battery-powered and designed for extended measurement sessions, lasting from a few hours to several days, and in

Table 2
Technical specifications of commercial and lab-built exposimeters.

	ExpoM-RF 4	EME-Spy Evolution	PDE vest/helmet Vanveerdeghem et al. (2015), Thielens et al. (2016, 2017)	González et al. (2021)	mm-PEM (Aminzadeh et al., 2017, 2018)
Sampling rate	Min 2–4 s	2 s	1 s	1 s	1 s
# Frequency bands	25	20	1	Multiple	1
Dynamic range	60 dB	56 dB	80 dB	90 dB	
Max. E-field/ power	6–60 V/m	6 V/m		20 dBm	
Sensitivity	0.005–0.010 V/m	0.02–0.05 V/m		−70 to 20 dBm	
Detector	True-RMS + envelope peak		Diode-based RMS	Logarithmic	
Antenna	Triaxial	Triaxial	Multiple dual-polarized patches/4 monopoles	Array of 5 fractals	four-patch single-layer array
Measurement time	50 ms			46.22 ms	
Isotropic uncertainty		+/−1.5 dB below 4 GHz +/−2.5 dB above 4 GHz			
Crosstalk	−40 to −60 dB				

some cases, up to a week. The antennas used may include monopole antennas or sets of multiple monopoles oriented in different directions to approach isotropy. Commercial devices are available, and different research laboratories have constructed their own devices for specific applications. Table 2 lists the relevant technical specifications of both commercial (the ExpoM-RF 4 and the EME-Spy Evolution) and lab-built exposimeters which will be discussed in Section 4.2.4.

Two prominent lines of commercial devices are commonly found: the ExpoM-RF series (Fields at Work) and the EME-Spy series (Microwave Vision Group). The most recent models in these lines are the ExpoM-RF 4 (Anon, 2023m) and the EME Spy Evolution (Anon, 2023e), respectively.

The ExpoM-RF 4 is capable of measuring at up to 25 customizable center frequencies, ranging from 50 MHz to 6 GHz, with bandwidth options of 35, 75, or 100 MHz. It allows users to set the maximum measurable field strength, though this affects sensitivity. The sensitivity for 6 V/m measurements falls within the range of 0.005 to 0.010 V/m, with variations across different frequencies. Users can define the sample interval, with the shortest interval being 2 s for 10 frequency bands and up to 4 s for 25 bands. Notably, the ExpoM-RF 4 introduces a spectrum analyzer mode, distinguishing it from previous versions.

An important distinction of this latest version lies in the fact that the ExpoM-RF 3 only measured using true-RMS with an integration time of 0.3 s (Anon, 2023f), while the ExpoM-RF 4 performs both true-RMS and envelope peak field strength measurements simultaneously within a 50 ms time interval. The specific post-processing method to combine these two measurements into a single E value is not specified, but this information may be available from the manufacturer. The device employs a triaxial isotropic antenna.

The EME Spy Evolution empowers users to monitor their choice of up to 20 frequency bands from a selection of 80 fixed options. These options encompass various bandwidths and center frequencies within the frequency range listed in Table 2. The exact sensitivity is contingent on the specific frequency. Users can define the sampling interval, with a minimum setting of 2 s.

As far as the authors are aware, there are presently no commercially available PEMs designed for FR2. Additionally, it is worth noting that both of the commercial devices mentioned earlier are equipped with a GPS logger.

4.2. Custom-developed instrument and sensors

4.2.1. Laboratory-designed broadband probes

A number of studies have reported on the design of custom-built broadband probes, typically in the form of compact dipoles equipped with Schottky diodes (Mavromatis et al., 2009, 2010; Živković et al., 2011; Viani et al., 2011; Leferink, 2013; Viani et al., 2016; Pinel et al., 2020; Ioriatti et al., 2009). These in-house developed probes exhibit similar attributes to their commercial counterparts, including sensitivity, dynamic range, and frequency range. Frequently, the intention behind creating these probes is to integrate them into cost-effective, compact, and self-sufficient measurement devices, i.e., as sensor nodes (Oliveira et al., 2006).

4.2.2. SDR-based sensor nodes

Spectrum analyzers, which operate in the frequency domain, may encounter limitations due to the inherent trade-off between frequency and time resolution. This limitations can make it challenging to differentiate between various signals that share the same frequency band but occur at different time intervals, like 5G-TDD uplink and downlink signals (Minucci et al., 2022). However, it has been demonstrated that a trade-off is achievable in some cases, as seen in Aerts et al. (2019).

In contrast, time domain instruments, such as real-time (spectrum) analyzers (RTA) and Software-Defined Radios (SDR), can overcome this frequency-related constraint. Between these two, SDRs are notable for their compactness, portability, and relatively lower cost in comparison to SAs and RTAs. As a result, SDRs could find application in large-scale deployments, such as sensor networks.

An SDR is a flexible RF communication system that can be employed for both transmitting and receiving RF signals. It enables the implementation of physical components like filters, attenuators, amplifiers, synchronizers, modulators, demodulators, and detectors in a digital form, positioned as close as feasible to the antenna (Santiago Rivera et al., 2018; Deprez et al., 2023). In this manner, the SDRs functionality is primarily dictated by software (e.g., utilizing GNU Radio), rather than hardware. This software-driven approach allows for dynamic adjustments to the SDRs operation and characteristics (Santiago Rivera et al., 2018).

Examples of SDR-based measurement nodes can be found in e.g., Santiago Rivera et al. (2018) (development of a digital FFT SA), Bechet et al. (2019) and Robert et al. (2021) (broadband field meter), Deprez et al. (2023) (measurement node for specific frequency bands), Minucci et al. (2022), and Sârbu et al. (2022) (isotropic broadband field

Table 3
Technical specifications of commercially available SDRs.

SDR	Frequency range	Resolution	Sample rate (MSPS)	Bandwidth (MHz)	Open source?	Cost (€)	Chipset
Adam-Pluto	325 MHz–3.8 GHz (70 MHz–6 GHz with software modification)	12 bit	61.44	20 (56 after software modification)	yes	250	AD9363
USRP E312	70 MHz–6 GHz	12 bit	61.44	56	no	6000	AD9361
RTL-SDR Blog v3	500 kHz–1766 MHz 22 MHz −2.2 GHz	8 bit	3.2	3.2	no	6000	RTL2832U
HackRF One	1 MHz–6 GHz	8 bit	20	20	yes	370	MAX5864
FreeSRP One	70 MHz–6 GHz	12 bit	61.44	56	yes	420	AD9364
LimeSDR	100 kHz–3.8 GHz	12 bit	61.44	56	yes	300	LMS7002M
BladeRF xA44	47 MHz–6 GHz	12 bit	61.44	56	no	540	AD9361
AntSDR E200 (1)	325 MHz–3.8 GHz	12 bit	61.44	20	yes	TED	AD9363
AntSDR E200 (2)	70 MHz–6 GHz	12 bit	61.44	56	yes	TED	AD9361

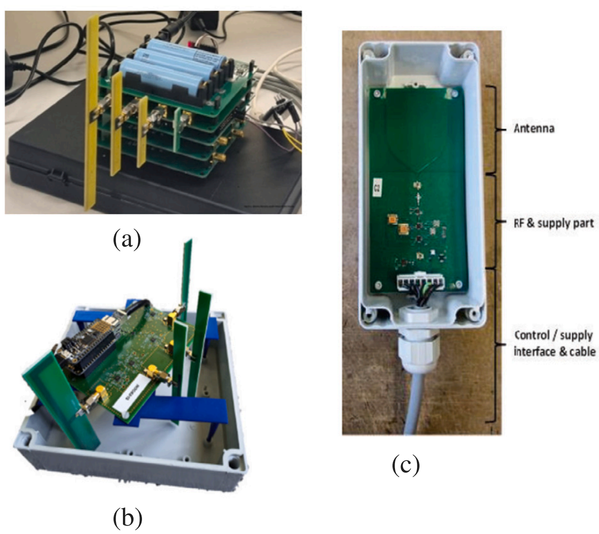


Fig. 2. Low-cost RF-EMF sensor nodes: (a) S^{3}R sensor node (Deprez et al., 2023), (b) WAVES sensor node (Deprez et al., 2023), (c) low-complexity dosimeter (Diez et al., 2014).

Table 4
Frequency bands of sensor nodes.

S^{3}R sensor node [MHz]	WAVES sensor node [MHz]	Low-complexity dosimeter [MHz]
758–788 DL	791–821 DL	925–960 DL
1452–1492 DL	925–960 DL	1805–1880 DL
2110–2170 DL	1805–1880 DL	2110–2170 DL
3450–3750 DL	3550–3700 DL	2400–2483.5 WiFi

meter). Unfortunately, uncertainty analysis is lacking in all of the aforementioned studies.

A variety of commercially available SDRs offer diverse performance levels and price ranges, as summarized in Table 3. While many of these devices are primarily designed for GPS or satellite transmission bands, some also cover the 5G FR1 frequency bands. Utilizing SDRs in measurement nodes offers the advantage of readily available hardware, simplifying field deployment. Additionally, certain compact SDRs, like the Adalm-Pluto, are pocket-sized and can be controlled via MATLAB or Python environments, making them well-suited for deployment as measurement nodes.

The Adalm-Pluto is an intriguing choice due to its appealing features (Anon, 2023). Like all SDRs, it serves both as a transmitter (Tx) and receiver (Rx). It features an AD9363 chipset with an initial frequency range of 325 MHz to 3.8 GHz, but it can be expanded to cover 70 MHz to 6 GHz with a simple adjustment. This adjustment essentially tricks the device into recognizing the AD9363 as if it was a AD9364 with extended capabilities. With a comparable trick (Anon, 2023b) the sample rate of the Blade xA4 can be doubled by using 8 bit instead of 16 bit space for the numbers.

The Adalm-Pluto has a 12-bit ADC resolution, a detection limit of −98 dBm, and an impressive dynamic range exceeding 80 dB (Deprez et al., 2023). It supports the connection of two antennas, such as the example in Deprez et al. (2023) where a dual-band JCG401 antenna (covering frequencies from 828 MHz to 984 MHz and 1710 MHz to 2170 MHz) and a wideband W5150 antenna (ranging from 617 MHz to 6000 MHz) were used. Furthermore, it has the capability to store in-phase and quadrature (IQ) samples ("in-phase" and "quadrature" refer to two sinusoids that have the same frequency and are 90° out of phase). Alternatively, the software on the device allows for the conversion of IQ samples into another unit, specifically dBFS (decibels relative to full scale). Through software control, gain settings of up to 74.5 dB can be configured, either manually or using automatic gain control (AGC). When employing AGC, it is important to note that changes in the full-scale range necessitate device calibration with a known source to obtain meaningful physical values (Minucci et al., 2022).

4.2.3. Hardware-based compact measurement nodes

To achieve accurate spatiotemporal RF-EMF exposure maps, a significant number of densely-distributed sensors are necessary (Aerts et al., 2022). However, such an extensive sensor network is economically unfeasible with high-end, costly, and relatively bulky devices. As a solution, researchers are developing low-cost (priced below €300), compact, and energy-efficient sensor units tailored for specific FR1 frequency bands. These units are integral in establishing a continuous RF-EMF exposure monitoring system (Aerts et al., 2022; Diez et al., 2014; Deprez et al., 2021; Korkmaz et al., 2022; Kwon et al., 2023).

For instance, a dedicated measurement node optimized for 5G applications has been created by Korkmaz et al. (2023), enabling measurements across the four frequency bands intended for use in the Netherlands. Fig. 2 displays some examples of laboratory-built, budget-friendly RF-EMF sensor nodes. The S^3R and WAVES sensor nodes utilize in-house designed narrowband planar half-wavelength dipole antennas for each frequency band (Deprez et al., 2023), while the low-complexity dosimeter employs a printed PCB monopole antenna probe (Diez et al., 2014). It is important to note that all low-cost sensor node antennas are linearly polarized and exhibit omnidirectional radiation patterns.

Table 5
Overview of cardinal epidemiological studies using exposimeters.

Paper	Type of study	Type of PEM	Use of PEM
Roser et al. (2015)	Prospective cohort	Commercial	Carried by pax (3 days)
Cabré-Riera et al. (2022)	Prospective cohort (Mothers and Children's Environmental Health)	Commercial	Validation of EMF model
Choi et al. (2017)	Population-based birth cohort	Commercial	Carried by pax (1 day) Prospective cohort (SCAMP)
Huss et al. (2021)	Exposure measurements (ACCEDERA)	Lab-built +commercial	Comparison of measurement devices

The developed measurement nodes are specific to certain frequency bands (e.g., see Table 4 for low-cost sensor nodes (Aerts et al., 2022; Diez et al., 2014; Deprez et al., 2021; Korkmaz et al., 2022)). Typically, these sensors can measure up to four frequency bands used by GSM, UMTS, LTE, and/or 5G NR for downlink (DL) communications. In the design of these sensor nodes, bandpass filters are commonly employed for each band to suppress signals from neighboring and interfering bands. Depending on the desired sensitivity level, a low noise amplifier (LNA) may be utilized to adjust the RF power level within the power detector's dynamic range. There are two primary types of power detectors: logarithmic and (t)RMS. Logarithmic detectors convert the input RF power into a DC voltage that is directly proportional to the logarithm of the input, providing an output in decibels (dB). RMS detectors produce a DC output that is proportional to the RMS value of the signal. It is worth noting that using a true RMS detector is more accurate, as it takes into account the instantaneous values of the signal without assuming a specific waveform shape. The dynamic range of power detectors typically falls within the range of 56–70 dB for FR1 frequencies. The DC output is then sampled with an ADC and is converted into a power level (dBm) using a lookup table within a standard microcontroller.

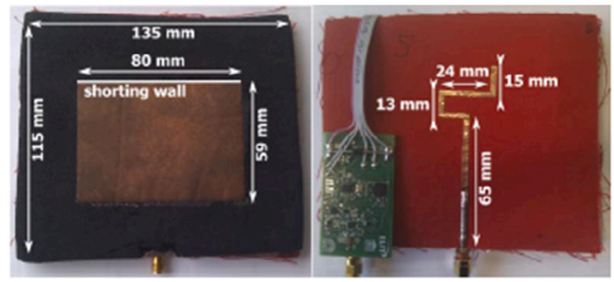
Similarly, in Viani et al. (2011, 2016), Ioriatti et al. (2009) cost-effective sensors for distributed EMF exposure assessment have been proposed. The sensors consist of three orthogonal dipole antennas, each featuring a diode detector to transform field values into a DC signal. Subsequently, with the use of an ADC and a microcontroller, these signals are converted into power or field values. It is worth noting that the sensors measure accurately within the frequency range of 200–5000 MHz (Viani et al., 2011).

All of the suggested EMF sensors are compact, budget-friendly, and user-friendly, requiring no specialized expertise for operation.

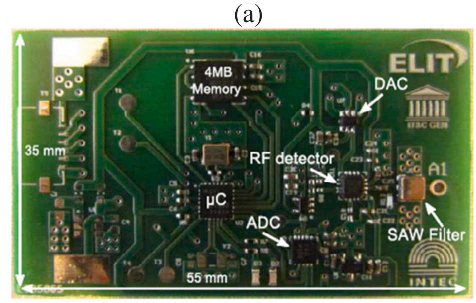
4.2.4. Lab-built exposimeters

In response to the inherent measurement uncertainties associated with commercial exposimeters, primarily stemming from body-shadowing effects, an on-body Personal Distributed Exposimeter (PDE) has been proposed, featuring multiple measurement nodes (see Table 2) (Vanveerdeghem et al., 2015). Each node is seamlessly integrated onto a textile antenna feed plane equipped with patch antennas. The PDE takes the form of a wearable vest, featuring multiple nodes distributed across various pockets. This particular PDE was tailored for the GSM downlink frequency band of 925–960 MHz, employing a logarithmic RF power detector with an impressive dynamic range of 80 dB. The PDE was designed with modularity in mind, accommodating up to 11 frequency bands (Vanveerdeghem et al., 2015; Thielens et al., 2016). Much like the sensors of the previous section, nodes consist of a bandpass filter, RF power detector, ADC, and a microcontroller. Fig. 3 depicts the PDE antenna and the processing unit. It is worth noting that the use of the PDE with untrained volunteers may be somewhat inconvenient. A similar design is employed for a drone-based RF exposure measurement system in Joseph et al. (2016).

In a related development, a PDE-helmet was introduced as part of a pilot project (Thielens et al., 2018). Based on simulations, it was determined that the human head experiences the least variation in E-fields and, consequently, the lowest measurement uncertainty. To capitalize on this, the PDE-helmet featured four monopoles positioned within a bicycle helmet in various orientations. This prototype also employed a diode-based RMS detector and was specifically designed for the 900 MHz GSM band.



(a)



(b)

Fig. 3. The PDE (Vanveerdeghem et al., 2015) consists of a number of distributed nodes with each (a) a textile patch antenna and (b) a processing unit.

A system resembling a spectrum analyzer while retaining the key benefits of conventional exposimeters was proposed in González et al. (2021). This system operates by assessing the highest received power level through the use of a logarithmic detector. It operates across a spectrum spanning from 78 MHz to 6 GHz, employing 300 kHz resolution bandwidths within numerous narrow bands. This configuration enables the system to identify various sources of electromagnetic fields. Each measurement takes place at one-second intervals, corresponding to 46.22 μs per frequency point. The frequency range is covered by an array of five fractal antennas sourced from Fractus Antennas, based in Barcelona, Spain. These antennas possess a wide bandwidth and are comparatively compact in relation to other types of commercial antennas. Notably, the system has a dynamic range of 90 dB with RF input power ranging from −70 to 20 dBm with a 0.04 dB resolution.

To date, only two research studies have been identified that detail the creation of custom-built measurement devices for evaluating RF-EMF exposure at frequencies within the FR2 range. These studies, documented in Aminzadeh et al. (2017, 2018), introduced two distinct versions of a mmWave personal exposure meter (mm-PEM) designed to operate at 60 GHz. The initial version featured a limited set of wearable antennas designed for placement on a forearm (Thielens et al., 2016). These wearable antennas were based on a microstrip-fed four-patch single-layer antenna array originally developed for applications in body area networks (BANs) (Chahat et al., 2012). In the second study, the mm-PEM was specifically evaluated for its effectiveness in assessing exposure within indoor diffuse fields (Aminzadeh et al., 2018).

4.2.5. Cardinal research on human studies

In contrast to PEMs, high-end measurement devices (mainly) used for spot measurements, such as spectrum analyzers and broadband field meters, are not typically used in epidemiological studies since they only provide measures of the exposure at a limited number of points in space and time. In fact, the authors are only aware of two (cross-sectional) studies in which a health or behavior outcome is related to RF-EMF spot measurements (Calvente et al., 2015; Meo et al., 2018). Moreover, the authors have no knowledge of any published epidemiological studies making use of RF-EMF sensor networks for their exposure assessment.

In Bartosova et al. (2021), an SDR is proposed as a source for dosimetry studies, emphasizing the importance of generating reproducible results using the SDR as the radiation source. A HackRF One SDR was employed in a study to measure electromagnetic leakage from household appliances (Perotoni et al., 2022). Additionally, various SDRs have been used for ElectroSmog measurements in a 5G network (Minucci et al., 2022). In Robert et al. (2021), an advanced and relatively expensive 3-axis system featuring a USRP-N310 SDR platform was utilized to measure RF fields emitted by an LTE-band telephone.

On the other hand, PEMs have been used in some of the recent big epidemiological studies (Bodewein et al., 2022). Table 5 lists some cardinal examples of these studies. The personal exposure of the participants is assessed using a combination of measurements with PEMs and questionnaires, quantifying the participants' exposure based on their use of mobile devices Roser et al. (2015), Cabré-Riera et al. (2022) and Toledano et al. (2018). In Cabré-Riera et al. (2022) the exposure is assessed using a questionnaire and geospatial modeling of EMFs from base stations. The PEMs were used in a microenvironmental measurement campaign to validate these models. Participants are instructed to carry the PEM with them in their daily life for a specified duration (1–3 days), and might be instructed to keep a diary (Roser et al., 2015; Toledano et al., 2018). To our knowledge, no lab-built exposimeters have been used in large scale epidemiological studies. However, in Huss et al. (2021), a lab-built body-distributed-exposimeter (BDE) was used in parallel with a commercial device. The conclusion was that due to body shielding, commercial exposimeters report slightly lower exposure values. This is informative for the interpretation of existing epidemiological research results.

5. Mobile phone based tools

A number of mobile phone applications (apps) have been developed to evaluate various parameters of mobile phone networks, including the 5G NR network. It is also proven feasible to use them for RF-EMF exposure assessment purposes (Amini et al., 2023). Some of these apps can also act as the interface between the network and a robust RF-EMF monitoring devices (e.g., spectrum analysers or network scanners).

Table 6 lists the apps, measured parameters, and their applications in 5G NR exposure assessments. Some of the key parameters measured by them are Physical Cell IP (cell ID or PCI), Global Positioning System (GPS) location, Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal-to-Noise and Interference Ratio (SINR), DL bandwidth, etc. Some of these parameters have been described in literature of RF-EMF exposure assessment (e.g., Brzozek et al., 2019; Minovski et al., 2021; Stevens and Younis, 2022; Amini et al., 2023). The 5G NR specific physical layer parameters, which make the basis for estimating RF-EMF exposures, are briefly introduced before discussing some of the apps utilized in scientific studies (Anon, 2023l).

Azenqos™ (AZQ) mobile network test app APK provides measurement and optimization solutions for 5G NR mobile networks (Anon, 2023c). It can be installed on a selected Android phones ((Anon, 2023c; Homayouni et al., 2022; Chobineh et al., 2018), to undertake 5G NR signal characterization (Anon, 2023a)). The app has been applied in characterizing DL and UL exposure in non-5G networks (Chobineh et al., 2018).

TEMS™ Pocket, a commercial state-of-the-art phone-based tool from Infovista, monitors the performance of wireless mobile networks on a millisecond level basis (Anon, 2023o; Minovski et al., 2021). The tool has been used to undertake RF testing that collects data on RF parameters for mobile networks, including both sub 6 GHz and mmWave 5G NR (Stevens and Younis, 2022; Minovski et al., 2021).

Qualipoc Android™ is based on commercial Android smartphones or tablets. The data recorded by the app are stored on the handset and can be downloaded into a CSV file. The QualiPoc also connects with a network scanner (e.g., R&S TSMA6 scanner or SA SRM-3006) and the combined parameter values (e.g., SSB signals data) can be used to characterize RF-EMF exposure levels in different situations. For example, Qualipoc-installed mobile phone was used to control 5G NR signals (e.g., under data download/upload) and gather 5G NR network information, which was then combined with RF-EMF exposure data collected with SRM-3006 spectrum analyser to estimate maximum electric field strength of 5G NR signals (Chountala et al., 2021). Similarly, the Qualipoc tool, along with R&S TSME network scanner, was used to measure and characterize maximum signal strength of 5G NR (3.68 GHz) traffic beam at the measurement point or UE (Adda et al., 2020). Further, in Sali et al. (2022) the application of QualiPoc is demonstrated in code-selective measurement of 5G NR (3.5 GHz) multiple-input and multiple-output (MIMO) network in Malaysia. This measurement approach allows in determining the maximum possible RF-EMF emission per PCI and SSB due to its decoding signal feature. QualiPoc can also be used to validate new proposed hardware tools for personal RF-EMF exposures assessment, such as an 'add-on sensor', which can be attached to a mobile phone handset as described by Van Bladel et al. (2023), Stroobandt et al. (2023) . Through this approach, human exposure could be evaluated under different mobile phone usage scenarios. A good agreement for uplink exposure was reported with a RMS error of 3.17 dB between the in-situ calibrated add-on sensor and QualiPoc (Stroobandt et al., 2023). This demonstrates a real-life application of Qualipoc in measuring RF-EMF exposures and validating other devices under development (Sae et al., 2019)

Nemo Handy™ is an Android-based mobile app, which enables measurement of key radio-frequency parameters of wireless and radio networks, including 5G NR up to 40 GHz (Anon, 2023q; Mazloum et al., 2021). The app can be installed on any commercially available Android smartphone and support the assessment of 5G NR exposure parameters. The app has been demonstrated its applicability in the evaluation of 5G NR (3.5 GHz) signal parameters (Milde and Pilinsky, 2022). Similarly, in Hoppari et al. (2021) performance of 5G NR (3.5 GHz) and Wi-Fi networks (2.4 and 5 GHz) with the Keysight Nemo Handy app are evaluated. In Sitindjak et al. (2021) Nemo Handy app is used as a benchmark tool while evaluating performance of freely available apps, G-Net Track Lite (Anon, 2023n) and Net Monitor Lite (Anon, 2023r), in terms of reporting results of LTE 3G network parameters.

SigCap™ is another app developed by the researchers at the University of Chicago, which collects data on various 4G and 5G NR physical layer parameters (see Table 6) (Anon, 2023w; Sathya et al., 2022). The app was used to evaluate the impact of small cell LTE on Wi-Fi data transmission, and to create 5G NR cell map in Chicago (Anon, 2023t).

Network Signal Guru™ (NSG) is a commercial Android app which uses mobile phone's root capability to gather similar physical layer measurement data of 5G NR network. Therefore, it provides more data on 5G NR specific parameters compared to those provided by SigCap (Rochman et al., 2022). These two apps were used to compare 4G and 5G NR (mmWave) parameter values (See Table) of different carriers deployed in Chicago and Miami (Rochman et al., 2022). This could be relevant for the situation where 4G (as a primary channel) and 5G (as a secondary channel) base stations are co and/or nearby located, such as current mobile phone base station deployment in Australia.

G-NetTrack Pro™, non-rooted Android app was used to collate 5G NR network data, including RSRQ and RSRP of an Irish mobile

Table 6
Mobile phone applications available for 5G NR signal characterization and RF-EMF exposure assessment.

Instrument name (vendor)	Parameters measured	Frequency range	Applications in RF signal or exposure characterization
Azenqos™ (Anon, 2023c) (Freewill FX, Bangkok, Thailand)	Frequency, PCI, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, Tx [dBm]	900, 1800, 2100 and 2600 MHz	Homayouni et al. (2022), Anchuen et al. (2021), Chobineh et al. (2018), Aerts et al. (2015), Mazloum et al. (2018)
TEMS™ Pocket (Anon, 2023o) (Infovista, Billerica, MA, USA)	Frequency, PCI, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm]	3.5 GHz, 27.5 GHz	Minovski et al. (2021), Stevens and Younis (2022), Sae et al. (2019), Zhohov et al. (2018)
QualiPoc Android™ (Anon, 2023v) (R&S,Munich, Germany)	Frequency, PCI, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm]	3.5 GHz, 3.68 GHz	Stroobandt et al. (2023), Van Bladel et al. (2023), Chountala et al. (2021), Sae et al. (2019)
Nemo Handy™ (Anon, 2023q) (Keysight, USA)	Frequency, PCI, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm]	3.5–40 GHz	Milde and Pilinsky (2022), Sitindjak et al. (2021), Mazloum et al. (2021), Sae et al. (2019), Hoppari et al. (2021)
SigCap (Anon, 2023w) (University of Chicago, IL, USA)	PCI, primary cell Bandwidth, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm]	5G NR mmWave network	Sathya et al. (2022), Rochman et al. (2022, 2021)
Network Signal Guru (Anon, 2023s) (Qtrun Technologies, Beijing, China)	PCI, Frequency, bandwidth, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm], resource block allocation, MIMO mode	5G NR mmWave network	Rochman et al. (2022, 2021)
G-NetTrack Pro (Anon, 2023n) (Gyokov Solutions, Sofia, Bulgaria)	Frequency, PCI, SS-RSRP (RSRP[a]) [dBm], SS-RSRQ (RSRQ[a]) [dB], SS-SINR (SINR[a]) [dB], GPS, [dBm], Tx [dBm]	3.5 GHz, 5G NR mmWave network	El-Saleh et al. (2022), Raca et al. (2020), Geng et al. (2019)

[a] Parameters specific to wireless/mobile network technologies other than 5G NR; GPS: Global Positioning System; Tx: uplink power of a User Equipment.

operator (Raca et al., 2020). This app can presumably use much lower data sampling time (e.g., 1 or 2 s) (Geng et al., 2019) compared to that of SigCap. The recorded data are automatically stored as logfiles (in text and KML formats) for further analysis including on the G-NetLook Web. Further, the app can also be used in assessing legacy mobile networks such as 3G and 4G; for example, collected mobile network signal and quality data (e.g., RSRP and RSRQ, etc.) in Saudi Arabia (El-Saleh et al., 2022).

5.1. Intercomparison and applications

There are only a few studies undertaking an intercomparison of these apps and/or validating the results with other tools. For example, in Sae et al. (2019) three apps (TEMS, Qualipoc and Nemo Handy) are used in characterizing LTE 800 signal associated RF-EMF exposure (e.g., UE Tx power). They conducted measurements with airborne UE's (smart phones attached to drones) and evaluated their impact on the ground level UE's in a rural environment. In Sae et al. (2019)it is claimed that the network parameters measured by different apps (i.e., TEMS Pocket, Qualipoc and Nemo Handy) do not affect the reliability of the results as each of them measure the same parameters, which are based on 3GPP specifications.

In Mazloum et al. (2021) two apps (i.e., AZQ and JDSU) were simultaneously used in measuring DL and UL RF-EMF exposures from 4G LTE macro and small cellular networks in two cities (Annecy, France; and Amsterdam, The Netherlands). They measured and compared performance of reporting downlink (RSRP) and uplink (UE Tx) exposures as a consequence of using both cellular network types. For the received exposure (RSRP) from macro cell, AZQ (compared to JDSU app) overestimated the exposure by 0.8 dB and 2.9 dB in Annecy and Amsterdam, respectively. For the small cell, AZQ overestimated the RSRP by 5.2 dB and 2 dB in Annecy and Amsterdam, respectively. For the UE Tx from macro cell, AZQ (compared to JDSU app (Anon, 2023p)) underestimated it by −3.3 dB in Annecy; and for a small cell it did so by −1.8 dB and −3.2 dB in Annecy and Amsterdam, respectively. The authors claim that difference in reporting exposure values by these two apps (mainly Tx value) can be due to the fact that AZQ accounted for the total Tx power (data and control signals), while JDSU only accounted for the signals carrying data. Viavi JDSU product (i.e., JDSU TrueSite Handheld app), which provided similar measures of the RF-EMF exposure parameters, has been discontinued (Anon, 2023p) and hence we did not provide further discussion on the app. However, similar intercomparisons of various apps, including 5G NR network data and different usage scenarios, would be valuable to enhance the understanding of 5G NR related RF-EMF exposures.

The applicability of these apps for human RF-EMF exposure assessment, including from 5G NR networks, seems promising. Since these apps provide valuable data on network parameters, such as received and transmitted power, they could be used in subsequent estimation of personal exposure for any exposure scenario or mobile technologies (in Aerts et al. (2013a) and in Mazloum et al. (2021)). These apps also provide valuable data on the physical layer parameters for both 5G NR and legacy technologies (such as 4G). While 4G technology is still in common use and 5G technology is its early deployment phase, a comparison of mobile network throughput of 4G and 5G NR technologies (Rochman et al., 2022), and associated RF-EMF exposures in different human environment could be undertaken. Such a study involving the fourth and 5th generation networks could provide valuable information on how much RF-EMF exposure is likely from 5G NR (compared to 4G), including mmWave in view of 5G NR network expansion.

5.2. Mobile applications on human studies

The mobile apps have been so far mainly used in different use case scenarios for RF-EMF signal characterization, particularly for legacy technologies but also for 5G NR services (to a lesser extent). Studies have tested these apps to measure RF-EMF signal parameters and/or demonstrate relationship between them in various human environments, which could be relevant to epidemiological studies; AZQ (Homayouni et al., 2022; Anchuen et al., 2021; Chobineh et al., 2018; Mazloum et al., 2018), TEMS, Qualipoc and Nemo Handy (Sae et al., 2019), Nemo Handy (Mazloum et al., 2018), and so on. To our best knowledge, we did not find any epidemiological studies that involve use of these apps. Earlier studies on RF-EMF exposure measurement have used XMobiSense™ app, which has been described elsewhere in literature. For example, XMobiSense™ was used to evaluate/validate RF-EMF exposure parameter or proxy measure of RF-EMF exposure such as recall of mobile phone usage (Goedhart et al., 2018) or self-reported mobile phone use (Goedhart et al., 2015) in human population samples, respectively. XMobiSensePlus™ is an updated version of the app unveiled for similar application (Mazloum et al., 2020). Quanta Monitor™, has been used in characterizing downlink and uplink (from a mobile phone handset) from mobile phones, however, its validation is limited in literature (Bhatt et al., 2018). We did not describe these apps for the reason that there is no clear indication that the apps could be used for assessing 5G NR related exposure parameters. The application of mobile apps for epidemiological studies could be possible through a direct estimation of exposure parameter values by using the apps in a sample of human subjects (e.g., pilot or validation studies) or use of the app collected data (e.g., through pilot or validation studies) in estimating personal or population RF-EMF exposures. A large-scale application of these apps in current and future epidemiological studies is challenging also because these apps are expensive.

6. Use cases

The different categories of measurement instruments discussed in the previous sections can be employed in various ways, each serving different objectives. The overall measurement uncertainty is influenced not only by the characteristics of the measurement device, as outlined earlier, but also by the specific measurement conditions, including methodology, environmental factors, and sources.

6.1. Stationary measurements

When an accurate assessment of RF-EMF exposure is required, such as for compliance assessments, measurements are typically conducted at one location at a time. These measurements last for the duration specified by international standards (e.g., ICNIRP, FCC/IEEE) or national legislation. Spectrum analyzers, often accompanied by an electric-field probe and a laptop, are commonly used for this purpose (IEC 62232:2022, 2022). Alternatively, broadband probes may also be employed in these spot measurements, either to obtain a rapid exposure level reading or to scan the area or volume to identify the location with the highest exposure (IEC 62232:2022, 2022).

Stationary measurements are associated with the lowest inherent measurement uncertainty since the measurement circumstances can be controlled to a great extent. Utilizing a SA, it is often possible to achieve an expanded uncertainty (at a 95% confidence interval) of ±3 dB, which includes the measurement conditions (e.g., Joseph et al. (2012a) referring to CENELEC). However, according to Kim et al. (2012), the expanded uncertainty in the context of "evaluating RF electromagnetic field exposure levels from cellular base stations" was estimated to be ±3.82 dB, encompassing measurement conditions. The primary contributor to this uncertainty is the calibration of the measurement device, with an uncertainty value of 3 dB. Unfortunately, Kim et al. (2012) does not provide further details on this aspect. In general, an expanded uncertainty of 4 dB is considered the "industry best practice" (ITU-K61, 2018).

When the experimenter carries the measurement device, such as a broadband field meter or a portable SA like the SRM-3006, in their hands, the impact of the experimenter's body can introduce additional uncertainty. According to Kim et al. (2012), the uncertainty associated with the influence of the body was determined to be 0.22 dB when the distance was between 1–2 m. It is worth noting that a maximum expanded uncertainty of +3.1 / −4.9 dB has been reported for the combination of the Narda SRM-3006 with the 3502/01 electric-field probe (Narda, 2018), although there is uncertainty regarding whether this figure includes measurement conditions like carrying the device.

6.2. On-body measurements

When there is a need for personal, on-body exposure assessment, the tools of choice are PEMs and measurement nodes, which can vary from exposimeters carried on the hip to a network of measurement nodes distributed over the body (Jalilian et al., 2019). These on-body measurements can also provide insights into in-body exposure, particularly in terms of the specific absorption rate (SAR) (Thielens et al., 2015). Over the years, on-body measurements have been instrumental in evaluating exposures in various microenvironments, involving volunteers or trained experimenters who carry these devices during their daily routines (Velghe et al., 2021; González et al., 2021).

When positioning measurement devices on the body, the body's influence can result in two opposing effects. On one hand, it may lead to an underestimation of exposure due to shadowing if the exposimeter is on the opposite side of the body from the source. On the other hand, it can lead to an overestimation due to constructive interference with waves reflecting off the body, especially when the exposimeter is in the line of sight of the source (Bolte et al., 2016). This necessitates the application of a body correction factor, which must be determined individually and tailored to specific microenvironments or activities, making it a complex factor to apply accurately (Bolte et al., 2016). Consequently, this contributes to a significant level of measurement uncertainty, ranging from a standard uncertainty of 5.3 dB to 12.2 dB (Bolte et al., 2016). To enable the comparison or combination of personal measurements, even from different units of the same type, systematic biases often need correction, typically through multiplicative correction factors, while striving to minimize measurement uncertainties (Bolte et al., 2016).

Table 7
Typical uncertainty values for commercial and custom-made broadband field meters and area monitors.

	Commercial	Mavromatis et al. (2009, 2010)	Viani et al. (2016)	Pinel et al. (2020)
Flatness of frequency response	1–5 dB	14.46% (1.2 dB)	2.6 dB	1.5–3 dB
Linearity deviation	0.3–3 dB	11.13% (0.9 dB)	4.1 dB	1.5 dB
Isotropic deviation	0.3–3.8 dB	3.54% (0.3 dB)	1.4 dB	not provided
Temperature response	0–1 dB	2.27% (0.2 dB)	0.45 dB	not provided
Modulation error	not provided	10% (0.8 dB)[a]	not provided	not provided
Crest factor error	not provided	10% (0.8 dB)[a]	not provided	not provided

[a] Typical values: BUWAL (Schweizer Bundesamt flir Umwelt, Wald und Landschaft): Mobilfunk-Basisstationen (UMTS-FDD), Messempfehlung, Entwurfvom 17.9.2003 (Mavromatis et al., 2009).

To reduce measurement uncertainty, two strategies have been recommended. One approach is to wear two PEMs on opposite sides of the body, which can result in an approximately 3 dB reduction in uncertainty (Thielens et al., 2014). Another approach involves using a PEM equipped with multiple antennas, sensors, or PDEs, as proposed in Thielens et al. (2013). Additionally, to specifically assess RF exposure in the head, a PDE-helmet was introduced in Thielens et al. (2018).

6.3. Vehicle-mounted measurements

When the objective is to gain a general understanding of the distribution of RF-EMF exposure across extensive geographical areas (or volumes) or to identify exposure hotspots, various types of measurement devices can be transported using vehicles, such as cars (Aerts et al., 2022; Bolte et al., 2016; Estenberg and Augustsson, 2013; Wang et al., 2022; Sagar et al., 2018; Onishi et al., 2023), drones (Joseph et al., 2016; Necz et al., 2021; García-Cobos et al., 2023), and bicycles (Thielens et al., 2018; González-Rubio et al., 2016). This approach to measurement is commonly referred to as the ’drive test method,’ and relevant recommendations can be found in ITU-T Recommendation K.113 (2015).

The position of the measurement device on the vehicle can significantly influence the measurement, requiring the determination of an additional vehicle correction factor (Bolte et al., 2016; Estenberg and Augustsson, 2013). However, there are (at least) two other factors that can impact the measurement result (Estenberg and Augustsson, 2013):

- The temporal variation of the field strength due to signal characteristics (e.g., pulsed signals in 2G-GSM and OFDM modulated signals in 4G-LTE and 5G NR) or multipath fading caused by reflections from moving objects.
- In most cases, the three electric field components are sequentially measured and then combined, with the distance between these measurements spanning several meters (e.g., 3–4 m in Wang et al. (2022)), determined by the sample rate and vehicle speed.

6.4. Distributed network measurements

To monitor the RF exposure over time, a distributed network of stationary measurement nodes (or sensors or sensor nodes) (Aerts et al., 2022; Estenberg and Augustsson, 2013; Diez et al., 2015), broadband probes (Iakovidis et al., 2022; Seyfi, 2013), (selective) area monitors (Iakovidis et al., 2022), or even commercial exposimeters (although only for 24 h) (Vermeeren et al., 2013) may be distributed over an area of any size. Aspects of remote monitoring are described in Šuka et al. (2015) – although they are outdated – and recommendations for monitoring of electromagnetic field levels are provided in ITU-K83 (2022), and recommendations on placement and analysis in Aerts et al. (2022).

These measurement devices can be installed in multiple ways, such as on building rooftops, street furniture, or on building facades (Aerts et al., 2022; Iakovidis et al., 2022). The height and specific placement of these devices can significantly affect measurements, particularly when placed near objects like walls or street lamps, which can introduce varying degrees of shadowing since exposure is commonly assessed at a 1.5 m height above the ground (IEC 62232:2022, 2022). For each measurement node, an “installation correction factor” is determined (Aerts et al., 2022; Iakovidis et al., 2022), accounting for these factors.

6.5. Measurement uncertainty

Commercial equipment datasheets typically include information on the following parameters, which may vary in detail: flatness of frequency response, linearity deviation, isotropic deviation, temperature response (though not always provided). The estimation of correction factors for non-standardized measurements is a necessary step for those factors, and it involves calibration through the measurement of a known electromagnetic field (Anon, 2013).

An extensive analysis of the uncertainty budget for broadband field meters was carried out in Oliveira et al. (2006), resulting in expanded uncertainties that range from 2.38 dB (excluding linearity) to 4.40 dB. This range incorporates additional uncertainty factors of 0.8 dB to 1 dB attributed to “absolute error” and 0.5 dB (equivalent to 15%) for “calibration”. The calibration values were derived from the calibration certificates provided by the products.

In the literature discussing laboratory-built devices, the treatment of uncertainty varied from being “absent” (Leferink, 2013) to being “fully detailed” (Mavromatis et al., 2009, 2010). The more comprehensive discussions yielded expanded uncertainties ranging from 1.9 dB to 2.5 dB, which appears lower in comparison to the values reported in Oliveira et al. (2006). An outline of typical uncertainty values is presented in Table 7.

As indicated in Celaya-Echarri et al. (2020), there is a lack of research on the measurement uncertainty associated with PEMs, although some studies have delved into this area, such as those by Bolte et al. (2011) and Blas et al. (2007). The primary sources of measurement uncertainties depend on the specific measurement scenario as described earlier. However, it is noteworthy that device-specific measurement uncertainties are often not disclosed by manufacturers, a trend observed for both commercially available and lab-built devices. For instance, Fields at Work notes a crosstalk between frequency bands ranging from −40 to −60 dB for the ExpoM-RF series but does not provide any information regarding uncertainties related to antenna isotropy, field strength linearity, frequency response flatness, and similar parameters.

6.6. Discussions regarding use in 5G exposure assessment

As of the current writing, there are four European projects (NextGEM (Petroulakis et al., 2023), SEAWave (Anon, 2024f), ETAIN (Anon, 2024b), GOLiAT (Anon, 2024d)) that constitute the European Research Cluster on EMF and Health (CLUE-H) (Anon, 2024a), which are actively conducting assessments of RF-EMF exposure in 5G networks (covering both FR1 and FR2).

These assessments involve the use of newly developed or cutting-edge measurement equipment (Minucci et al., 2022) and innovative or recently updated measurement protocols, whether standardized (IEC 62232:2022, 2022) or not (Velghe et al., 2021).

Following the deployment of commercial 5G NR networks various types of devices mentioned earlier have been employed to evaluate the electromagnetic fields emitted by the new BSs. For 5G-FR1, the same equipment can be used for assessing RF-EMF exposure within the frequency range up to 6 GHz, similar to their use in evaluating exposure in legacy networks (ranging from 2G to 4G). The exception is the need for a 5G-enabled mobile phone UE to induce maximum exposure conditions (Aerts et al., 2019) or at the very least, to assess auto-induced personal exposure (Velghe et al., 2021). For 5G-FR2, different probes for broadband field meters and spectrum analyzers, alternative antennas for measurement nodes, and other hardware such as harmonic mixers for spectrum analyzers are necessary.

To obtain a comprehensive evaluation of the theoretical worst-case exposures in 5G NR networks, specialized equipment like SAs or network scanners is essential. This is due to the significant stochastic nature of 5G NR wireless communications, which arises from factors like massive, interactive, and agile beamforming and a reduction in independently transmitted signals, affected by current traffic load and user behavior (Keller, 2019).

Current state-of-the-art techniques, whether frequency- or code-selective, rely on extrapolating measurements of signals that are independent of traffic load, such as the SSB. These methods are exclusively assessable using high-end measurement equipment (Fellan and Schotten, 2022). These techniques have been demonstrated for both FR1 and FR2, and a comprehensive overview can be found in Fellan and Schotten (2022).

It is worth noting that in the case of FR2, directive horn antennas are frequently employed rather than isotropic probes to increase receiver gain and mitigate the higher path loss at these high frequencies while minimizing the influence of the user equipment (Celaya-Echarri et al., 2020; Minucci and Verbruggen, 2022; Wood et al., 2021; Chiaraviglio et al., 2022; Anon, 2021c; Liu et al., 2024), although this is not always the case (Wali et al., 2022). When using horn antennas, it is important to ensure dual-polarized measurements, either by using a dual-polarized antenna or by turning a single-polarized antenna (Celaya-Echarri et al., 2020). In the case of single-axis omnidirectional antennas (Wali et al., 2022; Liu et al., 2024), rotating the antenna is necessary to ensure accurate measurements for different polarizations (Celaya-Echarri et al., 2020). However, measuring the RF-EMF in 5G networks as is (i.e., without extrapolation) is also done with the other types of measurement devices discussed previously.

Although it was noted in Letertre et al. (2013) that "diode-detector-based probes are unsuitable for signals with relatively high power and time variations" and subsequently demonstrated experimentally in Adda et al. (2022) that these probes tend to overestimate the amplitude of 5G-FR1 signals (by "tens of percent of the electric-field strength") due to their high crest factor, the use of broadband field meters is still recommended to ensure "a reliable assessment of the current total exposure" (IEC 62232:2022, 2022; Keller, 2019). In fact, several 5G-FR2 (operating at 26 GHz and 60 GHz) measurement campaigns have employed broadband field meters with isotropic probes (Wood et al., 2021; Agence Nationale des Fréquences, 2021; Ofcom technical report, 2020), despite their sensitivity limitations (at least 0.7 V/m) and the challenges posed by the large signal bandwidth (Adda et al., 2022).

Moreover, the latest generation of commercial PEMs can now measure the 5G-FR1 bands (Selmaoui et al., 2021). However, due to the growing importance of auto-induced exposure, PEMs alone are no longer sufficient to assess personal exposure, necessitating the use of additional equipment like a mobile phone (Velghe et al., 2021). Unfortunately, there is currently a lack of published data regarding the reliability of PEMs when measuring 5G-FR1 signals. Furthermore, there are no commercially available exposimeters for the 5G-FR2 band. In Thielens et al. (2017), the feasibility of PEMs for mmWaves was discussed, and in Anon (2023m,e) two different versions of a mmWave personal exposimeter (mm-PEM) are introduced operating at 60 GHz, although these have not been field-tested. Similarly, the PDE has not been adapted to measure 5G-FR1 bands.

The 5G-FR1 bands can be measured directly by many European measurement networks, comprising area monitors equipped with broadband probes that can measure up to 7–8 GHz (Iakovidis et al., 2022), or broadband measurement nodes (Iakovidis et al., 2022; Pinel et al., 2020), with no need for specific modifications. Nevertheless, they encounter similar limitations as broadband field meters because the probes they employ also incorporate diode-based detectors.

Lastly, the most recent versions of lab-built measurement nodes either encompass some of the 5G-FR1 bands (Minucci et al., 2022) or are purpose-built to exclusively measure the 5G-FR1 bands (Santiago Rivera et al., 2018). It is important to mention that when designing these nodes, tRMS detectors are the preferred choice (Minucci et al., 2022). As far as the authors are aware, there are no measurement nodes available, whether commercially or in a lab setting, that are capable of measuring the 5G-FR2 bands at the moment.

7. Conclusions

The objective of this review was to establish a groundwork for progress in the field of RF-EMF exposure assessment, ultimately contributing to a more thorough and efficient assessment. This review provides a comprehensive overview of the current state-of-the-art concerning RF-EMF measuring instruments. It covers a wide array of tools, such as spectrum analyzers, broadband field meters, area monitors, personal exposimeters, and custom-built instruments, as well as the existing measurement protocols, encompassing both standardized and non-standardized methods. In addition, we also have presented some of the most commonly used mobile apps for collecting 5G NR radio network data, which have also been used in RF-EMF exposure assessments. However, it is not yet clear on how accurate the measurement results of these apps are and how they compare among themselves and to more sophisticated tools.

Most importantly, this review revealed the need for cost-effective and long-lasting measurement devices or sensors that are capable of collecting data at a high time resolution in various frequency bands, as well as withstanding various environmental conditions. These sensors are essential for conducting stationary, mobile, and personal exposure assessments across larger geographical areas, time intervals, and populations than current capabilities allow. Additionally, it is important to recognize that the specific requirements for these sensors differ based on their intended usage, e.g., on-body measurement devices need to take into account the influence of the body, vehicle-integrated sensors the influence of the speed and the relative position of the sensor on the vehicle, and sensors on infrastructure the influence of the height and the building materials. Furthermore, there exists a demand for real-time, fast-sampling solutions to comprehend the highly irregular temporal variations in EMF distribution within next-generation networks.

Moreover, there is a notable absence of extensive information regarding currently employed custom-developed RF-EMF measurement tools, particularly with respect to measuring uncertainty. Considering the diversity of tools and methodologies in use, conducting a thorough comparison becomes crucial to identify the necessary statistical tools for aggregating the available measurement data.

A more in-depth discussion relating the current 5G NR assessment methods to measurement equipment is intended for a follow-up study, which will describe more in detail the requirements, opportunities, and priorities for new, low-cost, custom-built measurement equipment.

CRediT authorship contribution statement

Erdal Korkmaz: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sam Aerts:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Richard Coesoij:** Writing – original draft, Methodology, Investigation, Conceptualization. **Chhavi Raj Bhatt:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Maarten Velghe:** Writing – review &

Table A.8
Abbreviations table.

Abbreviation	Description
5G	Fifth-generation
ADC	Analog-to-digital Converter
AZQ	Azenqos
BANs	Body Area Networks
dBFS	deciBels relative to Full Scale
DL	Downlink
DSP	Digital Signal Processor
EMF	Electromagnetic Field
GPS	Global Positioning System
ICES	International Committee on Electromagnetic Safety of the
IEEE	Institution of Electrical and Electronic Engineers
IQ	In-phase and Quadrature
ICNIRP	International Commission on non-Ionizing Radiation protection
IoT	Internet of things
FR1/2	Frequency Range 1/2
MaMIMO	Massive Multiple-Input Multiple-Output
mmWave	Millimeter Wave
NR	New Radio
MSPS	Megasamples per second
NSG	Network Signal GuruTM
PCI	Physical Cell IP
PDSCH	Physical Data Shared Channel
PEMs	Personal Exposure Meters
RF	Radio Frequency
RMS	Root-Mean-Square
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSSI	Received Signal Strength Indicator
Rx	Receiver
SAR	Specific absorption rate
SCHEER	Scientific Committee on Health, Environmental, and Emerging Risks
SINR	Signal-to-Noise and Interference Ratio
SSB	Synchronization Signal Block
tRMS	True Root-Mean-Square
Tx	Transmitter
UL	Up Link
V/m	Volt per meter
W/m2	Watt per square meter

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Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Appendix. Abbreviations

See Table A.8.

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