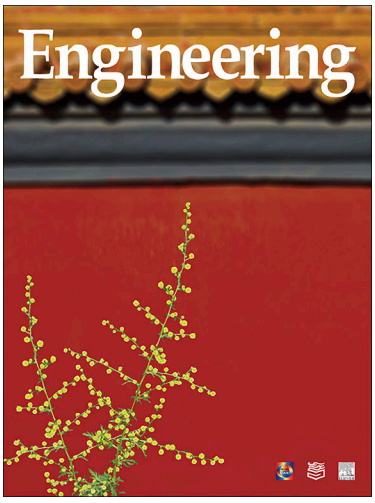
Journal Pre-proofs



Views & Comments

Trustworthy Biomedical Microwave Sensing for Long-Term Deployment

Chang-Hong Fu, Hong Hong

PII: S2095-8099(26)00609-0
DOI: https://doi.org/10.1016/j.eng.2026.10.010
Reference: ENG 2493

To appear in: *Engineering*

Received Date: 25 July 2026
Revised Date: 8 September 2026
Accepted Date: 19 October 2026

Please cite this article as: C-H. Fu, H. Hong, Trustworthy Biomedical Microwave Sensing for Long-Term Deployment, *Engineering* (2026), doi: https://doi.org/10.1016/j.eng.2026.10.010

This is a PDF of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability. This version will undergo additional copyediting, typesetting and review before it is published in its final form. As such, this version is no longer the Accepted Manuscript, but it is not yet the definitive Version of Record; we are providing this early version to give early visibility of the article. Please note that Elsevier's sharing policy for the Published Journal Article applies to this version, see: https://www.elsevier.com/about/policies-and-standards/sharing#4-published-journal-article. Please also note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2026 THE AUTHORS. Published by Elsevier LTD on behalf of Chinese Academy of Engineering and Higher Education Press Limited Company

Trustworthy Biomedical Microwave Sensing for Long-Term Deployment

Chang-Hong Fu, Hong Hong *

School of Electronic and Optical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China

* Corresponding author.

E-mail address: hongnju@njust.edu.cn (H. Hong).

1. Introduction

Contactless biomedical sensing is moving from controlled laboratories into the messier environments of clinics, vehicles, and homes. Biomedical microwave sensors, including Doppler, frequency-modulated continuous-wave (FMCW), and ultra-wideband (UWB) radar, can monitor cardiopulmonary micromotion and body activity without skin contact or wearable devices and are thus becoming part of ambient intelligence for healthcare [1,2]. Unlike cameras and microphones, microwave sensors do not directly record recognizable images or speech. This difference matters in private care environments, such as bathrooms, where cameras or microphones may be unacceptable.

Long-term deployment nevertheless changes the engineering target. Accuracy remains essential, but users and clinicians must also understand when sensing is active, how the device operates, and where physiological data travel. A system that performs well against a short-term benchmark may still fail at home because of undocumented exposure conditions, calibration drift, or unrestricted data export. In a prospective ten-night radar-based home sleep study, night-to-night variability was substantial, measurements failed on 16% of nights, and single-night assessment produced meaningful diagnostic misclassification [3]. Recent clinical-scale radio-sensing studies likewise emphasize diverse cohorts and cross-modal transfer rather than single-site accuracy alone [4,5].

The deployment question is therefore whether biomedical microwave sensing can remain trustworthy when it operates for hours each day in private and clinically consequential spaces. Earlier medical-radar work addressed tissue properties, antenna coupling, and electromagnetic compatibility [6], while responsible ambient sensing already considers privacy, consent, and fairness [1,2]. Building on this work, we propose two coupled design boundaries: an exposure boundary for radio-frequency (RF) energy and a data boundary for physiological information. These boundaries motivate exposure-aware design and a nodes–edge–cloud architecture that keeps raw sensing data close to acquisition while enabling authorized longitudinal and clinical use. We examine how to select them together under task requirements using a quantitative formulation and measurable criteria. The boundaries are not independent: Increasing sensing range, resolution, or duration may change both the energy delivered to a space and the physiological detail that can be reconstructed.

2. Why exposure and privacy should be designed together

Biomedical microwave sensing is often described as low-power, contactless, and privacy-preserving. Each description requires qualification. Active radar intentionally transmits RF energy, whereas passive radar can reuse existing Wi-Fi illumination [7,8]. Moreover, the absence of recognizable imagery does not eliminate privacy risk: Radar returns may reveal presence, posture, gait, sleep regularity, breathing dynamics, and daily routines. Cameras and microphones provide useful privacy comparators because they additionally capture identity, visual context, or speech, but they are not the focus of the proposed architecture.

Physical safety and information governance are linked by the sensing design. Frequency, waveform, antenna pattern, beam steering, duty cycle, and distance determine signal quality and the exposure envelope. The same choices shape spatial resolution and the information contained in raw in-phase and quadrature (I/Q) data, radar cubes, range–Doppler maps and derived trajectories. Sparse measurements can therefore accumulate into a sensitive health and behavior profile even when faces and voices are absent. Greater bandwidth, aperture, or observation time may improve a clinical estimate while simultaneously enlarging one or both boundaries.

A task-oriented approach helps set both boundaries. Respiration-rate estimation may not require continuous transmission, high spatial resolution, or raw-data upload. Fall detection requires reliable event recognition but not indefinite storage of micro-Doppler signatures [9,10]. Nightly sleep monitoring makes duty cycle, calibration, retention, and user control more important than such monitoring in a supervised trial [3–5]. In Fig. 1, the exposure boundary progresses from sensing source and human interaction to operating control and safety evidence, while the data boundary progresses from signal and device layers through a trusted edge to authorized services. Health task, deployment setting, and user context should jointly define

the minimum sufficient energy and minimum sufficient information. In practice, the designer can reduce transmit power, duty cy[Journal Pre-proofs]on 6 formalizes this selection.

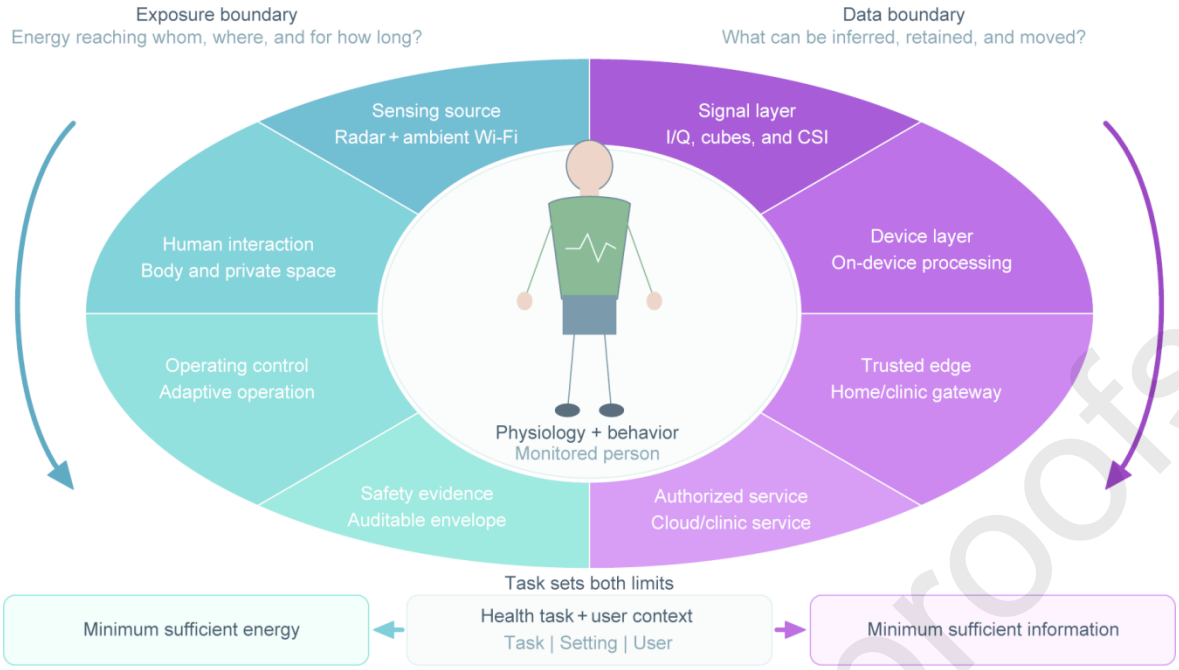


Fig. 1. Coupled trust boundaries for long-term biomedical microwave sensing. The exposure boundary links the sensing source and human interaction to operating control and safety evidence. The data boundary links signal and device layers to a trusted edge and authorized services. Health task, deployment setting, and user context determine the minimum sufficient energy and information (Section 6). CSI: channel state information.

3. Exposure-aware biomedical microwave sensing

The 2020 International Commission on Non-Ionizing Radiation Protection (ICNIRP) guidelines cover RF electromagnetic fields from 100 kHz to 300 GHz, while Institute of Electrical and Electronics Engineers (IEEE) Std C95.1-2019 defines safety levels from 0 Hz to 300 GHz [11,12]. These guidelines and standards provide health-based restrictions, reference levels, and assessment concepts but do not certify a biomedical radar product or installation. Their role here is to define the external safety envelope that an exposure-aware system must characterize. Regulatory compliance concerns applicable requirements, while biological safety requires dosimetry and health evidence. Trustworthiness additionally includes clinical reliability, privacy, and user control. Compliance alone therefore does not establish suitability for long-term use.

Published systems illustrate why generic claims of low power are inadequate. A 24.17 GHz continuous-wave heart-sound radar reported a measured equivalent isotropically radiated power (EIRP) of about 18 dBm [13]. A Nanjing University of Science and Technology (NJUST) digital-intermediate frequency (IF) Doppler radar reported vital-sign measurement within 3 m at –13 dBm transmit power [14], whereas a low-IF dual-phase-locked-loop (PLL) design with RF-leakage cancellation reported 4 m sensing at –31 dBm [15]. These values are not directly comparable because the systems were evaluated under different operating conditions. Hardware reviews document this diversity [16]. A synchronized reference dataset supports comparisons of signal recovery [17], but it does not make exposure assessments comparable. Compliance, however, remains installation-specific. A transmit-power value is informative only when the operating conditions and installation are also reported.

A radar used for months in a bedroom creates a different exposure case from one used briefly in a supervised laboratory. This distinction matters most for occupants who have little practical control over the sensor, including infants, children, older adults, and some patients [18,19]. Fig. 2 also shows that several radars may operate with the home's Wi-Fi. The exposure case is therefore defined by the occupied space and operating schedule, including source concurrency, field distribution, and sensor placement. Output power alone cannot characterize this exposure case. Duration should be assessed using the applicable averaging windows, not a lifetime sum of transmitted energy.

For N transmitting antennas with mutually incoherent emissions in a free-space far field, the time-averaged incident power density $\overline{S}$ at observation position x is approximately

Journal Pre-proofs

$$= \sum_{i=1}^{N} \frac{\mathrm{EIRP}_i \, F_i(\Omega_i) \, d_{i,W}}{4\pi \, r_i^2} \quad (1)$$

where N is the number of transmitting antennas included in the assessment, Ω_i denotes the angular direction from antenna i toward the observation position x, P_i is the constant on-state conducted transmit power supplied to antenna i, and r_i is the distance from that antenna to x. The transmitting fraction of antenna i over an averaging window of duration W is denoted by $d_{i,W}$. The linear gain toward x is $G_i(\Omega_i) = G_{i,\max} F_i(\Omega_i)$, with a maximum gain $G_{i,\max}$ and a power radiation pattern F_i normalized to a maximum of 1. In Eq. (1), $\mathrm{EIRP}_i = P_i \, G_{i,\max}$ denotes the maximum-direction EIRP, so the second expression simply substitutes this factorization. The incident energy per unit area over W is $W\,\overline{S}(x)$.

Near fields, reflections, and coherent sources require suitable field measurements or modeling. Compliance must follow the applicable frequency-dependent quantities, averaging conditions, and multi-frequency rules [11,12]. As an illustrative scaling result, halving all duty cycles halves $\overline{S}(x)$, and doubling all distances reduces it fourfold under Eq. (1).

We therefore argue that an exposure-aware design should document the installation before claiming compliance. At minimum, a study should report the operating frequency, conducted transmit power and EIRP, antenna pattern, duty cycle, distance, measurement duration, and intended installation. Those data can then support adaptive control: Power or duty cycle can be lowered once the required signal quality is reached, and spatial resolution can be limited when the health task does not need it. Antenna research provides two useful implementation precedents: Constrained aperture-illumination synthesis can limit peak radiation outside an intended collection region, and retrodirective arrays can automatically track a source while reducing the beam-pointing error [20,21]. Translating these capabilities to biomedical sensing will require human-centered exposure validation rather than assuming that spatial focusing is intrinsically safe. Long-term reliability also requires calibration and artifact control [22], because an unstable system may compensate with unnecessary energy or repeated acquisition. In multi-node homes, the control policy should also coordinate simultaneous transmissions and record the assumptions used to estimate aggregate exposure. Exposure metadata should become part of reproducibility, alongside accuracy and datasets.

4. Physiological privacy beyond visual anonymity

Radar and Wi-Fi sensing are often called privacy-preserving because they do not directly capture recognizable images. Yet they can infer whether a person is present, asleep, restless, short of breath, or deviating from a baseline. Under the European Union's General Data Protection Regulation (GDPR), health data receive special-category protection, as do biometric data when used for unique identification [23]. The GDPR is therefore a useful example of why physiological inference is sensitive, not a universal device-safety standard.

Optical and acoustic sensing clarify the relative privacy advantage of microwave sensing. Facial video used for remote photoplethysmography contains identity, expression, skin tone, and scene context; physiological leakage can itself require suppression [24]. Microphones used for breathing or cough monitoring may also capture speech. Microwave sensing avoids those direct visual and acoustic records, but its derived physiology still needs protection. IEEE Std 802.11bf-2025 formalizes wireless local area network (WLAN) sensing enhancements, making it possible for familiar communication infrastructure to act as a sensor without an obvious change in appearance [25,26].

Data protection should follow information content rather than modality labels. Raw I/Q signals, radar cubes, channel state information, and beamforming feedback are high-risk. Range–Doppler maps, micro-Doppler signatures, trajectories, and respiratory waveforms remain sensitive. Low-dimensional outputs such as respiration rate, sleep trend, fall alarm, or apnea probability are more suitable for remote sharing, but only with a defined purpose, authorization, retention limit, and security control.

5. Nodes–edge–cloud architecture

Fig. 2 maps a multi-room deployment onto a nodes–edge–cloud hierarchy. In the figure, classes 2 and 3 are microwave-sensing nodes; class 1 combines Wi-Fi sensing and the home gateway, and classes 4 and 5 are optional optical and acoustic comparators. Active radar supports cardiopulmonary and breathing-disorder monitoring [27] and fall detection [9,10], whereas passive radar reuses existing illumination [7,8]. Optical and acoustic nodes remain purpose-bound comparators, not default components of a microwave-sensing system.

The data boundary becomes coarser at each upward step. Raw I/Q samples, radar cubes, and identifiable audio or video should remain at the device or home layer by default. The trusted home edge performs calibration, signal-quality control, event detection, local inference, and short encrypted retention. Routine release to cloud or clinical services is limited to authorized alerts, trends, or model updates. This release boundary should be explicit, testable, and reversible: A change of health task should require a new authorization rather than silently expanding data collection. Selected raw records may be

accessed remotely for specialist evaluation, algorithm validation, regulatory review, or retrospective clinical analysis, subject to [redacted] and access auditing.

Journal Pre-proofs

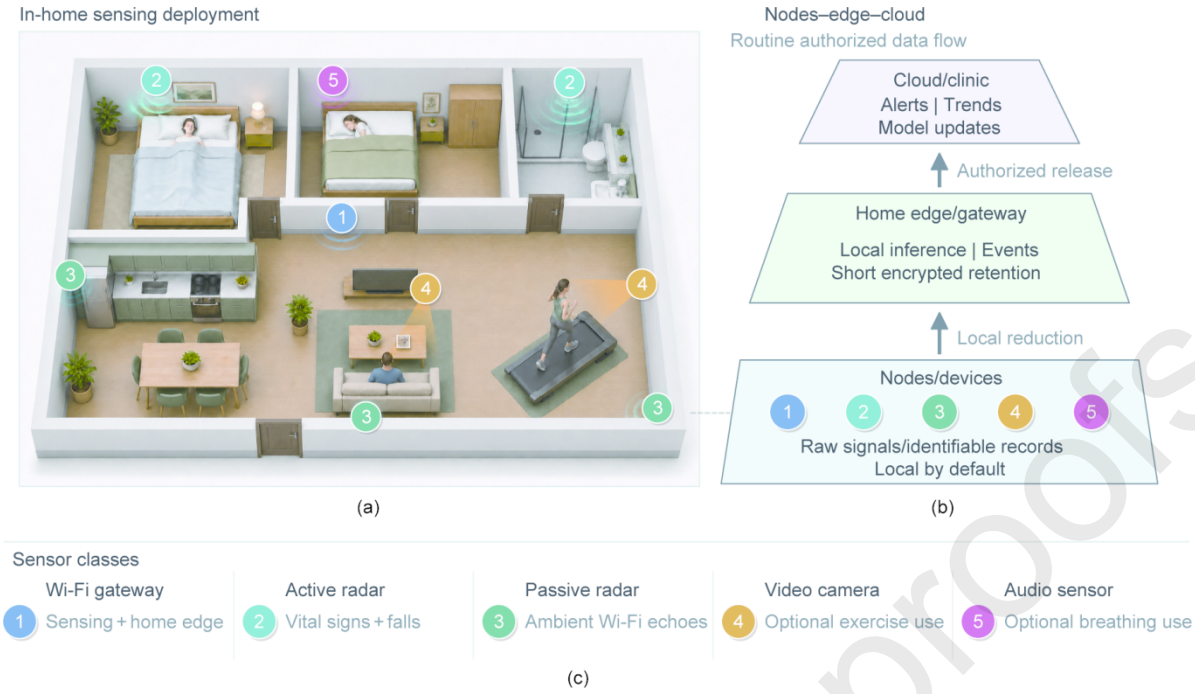


Fig. 2. In-home sensing nodes and the hierarchical nodes–edge–cloud data boundary. Device classes are ① central Wi-Fi gateway and sensing; ② active mm-wave radar; ③ passive radar using ambient Wi-Fi; ④ optional video for exercise monitoring; and ⑤ optional audio for breathing and snoring. Raw and identifiable data remain within the home by default, the edge retains quality-controlled features and events, and cloud or clinical services routinely receive authorized alerts, trends, and model updates. Controlled raw-data access exceptions are described in Section 5.

This hierarchy makes data minimization an architectural property rather than a later promise. Each node performs artifact rejection and feature extraction near acquisition; the home edge enforces household-level access and retention policies and fuses selected outputs only when the health task requires it. User control should also be implemented at the home edge. A resident should be able to see when sensing is active, pause it, and delete local records without relying on a cloud service. A camera exposes identity and room context, and a microphone may capture speech. These additional nodes therefore require separate, task-specific authorization.

The cloud is a secondary, task-bound layer, not a default raw-data repository. It is needed only for tasks that the home edge cannot complete, such as clinician review of long-term trends or multi-site model training. For the latter, federated learning keeps observations at each site and shares model updates. FedQ² provides a concrete example of quality-aware aggregation for motion-contaminated remote heart-rate monitoring [28]. Federated learning, however, does not eliminate model inversion, poisoning, or secondary-use risks; privacy controls and governance are still required [29]. The architecture must also treat cybersecurity failures as clinical hazards. US Food and Drug Administration (FDA) guidance on medical-device cybersecurity addresses device design and quality management across the product life cycle [30]. A compromised sensor could suppress an alarm, fabricate a measurement, or distort a reported clinical trend. For that reason, every output released upstream should carry provenance, signal-quality, and authorization metadata.

6. Engineering opportunities

Several engineering choices would make these boundaries operational. Exposure reporting should be accompanied by estimation error in every biomedical microwave study, so that performance can be interpreted under reproducible operating conditions. Privacy also needs a physical-layer expression: Task-specific waveforms, adaptive resolution, and constrained beamforming can reduce the information acquired before software policies are applied. Hardware and algorithms must then remain stable over long deployments; calibration drift or changing clutter should not lead automatically to more transmission, longer retention, or cloud processing. The useful design target is therefore an operating mode whose reductions in energy and data are measurable, testable, and tied to the health task.

For a fixed monitoring duration T, we let u specify acquisition, processing, retention, and release. For each choice of u, we assume constant on-state transmit powers over T. The conducted RF energy is $E_{\mathrm{tx}}(u) = \sum_i P_i(u) d_{i,T}(u) T$, where $d_{i,T}$ is its transmitting fraction over T. We define B_{ret} as the time-averaged number of stored bytes over T. A compact joint selection is

$$\min_{u \in U_{\text{adm}}} \left(E_{\text{tx}}(u),\ B_{\text{ret}}(u)\right) \quad (2)$$

Journal Pre-proofs

Because u also specifies data release, B_{out}—the total bytes released upstream over T—is reported alongside the two objectives but is not minimized separately in Eq. (2). The admissible set U_{adm} contains policies that meet prespecified clinical accuracy or sensitivity, failure-rate and latency limits, applicable exposure requirements, and authorized data handling with bounded inference leakage. B_{ret} measures retained data volume, not privacy itself. Here, "minimum sufficient" denotes a Pareto-efficient feasible policy (within the policies that meet the task, safety, and reliability requirements, neither energy nor retained data can be reduced without worsening the other). Thresholds depend on the health task.

A benchmark should expose these trade-offs, not hide them behind a single accuracy score. The Human Activity Radar Challenge has shown the value of common data and evaluation rules [31]. A deployment benchmark should add the conditions that determine trustworthiness: sensor placement, transmit settings, monitored population, environment, consent, retention rules, and known privacy risks. Systems could then be compared by safety margin, data minimization, robustness, and fairness, as well as accuracy. User control is equally technical: Continuous sensing in private spaces requires visible status, understandable consent, local deletion, opt-out mechanisms, and a clear account of what is and is not measured. Reporting failure rates and unavailable data is as important as reporting average performance, because long-term trust depends on predictable behavior under imperfect conditions.

A practical evaluation would compare fixed settings with power/duty-cycle and retention sweeps against clinical reference measurements. Exposure would be characterized first, followed by repeated sessions under placement or motion changes. Acceptance thresholds should be prespecified, with the measures reported in Table 1. This is a proposed evaluation, not a report of new experiments.

Table 1

Suggested measurements for joint selection.

Quantity or requirement	What to measure
Energy and exposure—Eqs. (1) and (2)	E_{tx} per session; incident power density at occupied positions; and compliance with applicable exposure limits
Retained data and privacy—Eq. (2)	Mean stored bytes B_{ret} and retention duration; total bytes released upstream over T (B_{out}); and inference or reconstruction success under stated attacker access.
Task performance and reliability—U_{adm}	Reference-based error or sensitivity and specificity; false alarms; and failed-measurement fraction and decision latency

7. Conclusions

Biomedical microwave sensing is entering a deployment stage. Its value will not be determined only by higher resolution, lower estimation error, or larger learning models but by whether systems are trusted to operate continuously in homes, clinics, vehicles and care facilities. Microwave engineers have particular leverage because electromagnetic waves interact with the body and private environment before any algorithm is applied. Exposure-aware safety envelopes, minimized physiological data movement, and nodes–edge–cloud control should therefore be treated as core system requirements. Long-term trustworthy deployment is not an afterthought to sensing performance; it is a design target in its own right.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (62471232, 62431013, and U24A20230).

References

[1] Haque A, Milstein A, Li FF. Illuminating the dark spaces of healthcare with ambient intelligence. Nature 2020;585(7824):193–202.

[2] Martinez-Martin N, Luo Z, Kaushal A, Adeli E, Haque A, Kelly SS, et al. Ethical issues in using ambient intelligence in health-care settings. Lancet Digit Health 2021;3(2):e115–23.

Journal Pre-proofs

[3] Tschopp S, Borner U, Caversaccio M, Tschopp K. Long-term night-to-night variability of sleep-disordered breathing using a radar-based home sle

[4] He H, Li C, Ganglberger W, Gallagher K, Hristov R, Ouroutzoglou M, et al. What radio waves tell us about sleep! Sleep 2025;48(1):zsae187.

[5] Zhuang Z, Xue B, An Q, Chu H, Zhang Y, Chen R, et al. Advancing sleep health equity through deep learning on large-scale nocturnal respiratory signals. Nat Commun 2025;16(1):9334.

[6] Narayanan RM. Technical considerations in medical radar. In: Proceedings of the 8th International Conference on Body Area Networks; 2013 Sep 30–Oct 2; Boston, MA, USA. Piscataway: IEEE; 2013. p. 526–35.

[7] Li W, Piechocki RJ, Woodbridge K, Tang C, Chetty K. Passive WiFi radar for human sensing using a stand-alone access point. IEEE Trans Geosci Remote Sens 2021;59(3):1986–98.

[8] Huang S, Zhao H, Hong H, Guo F, Peng M, Zhu X. A concurrent multibeam passive radar for respiratory detection from multiple subjects. IEEE Trans Microw Theory Tech 2025;73(8):4298–311.

[9] Ding C, Zhao H, Ma Y, Hong H, Zhu X. Soft fall detection with a height-tracking method based on MIMO radar system. IEEE Geosci Remote Sens Lett 2023;20:1–5.

[10] Su BY, Ho KC, Rantz MJ, Skubic M. Doppler radar fall activity detection using the wavelet transform. IEEE Trans Biomed Eng 2015;62(3):865–75.

[11] International Commission on Non-Ionizing Radiation Protection (ICNIRP). Guidelines for limiting exposure to electromagnetic fields (100 kHz to 300 GHz). Health Phys 2020;118(5):483–524.

[12] Institute of Electrical and Electronics Engineers (IEEE). IEEE Std C95.1-2019: IEEE standard for safety levels with respect to human exposure to electric, magnetic, and electromagnetic fields, 0 Hz to 300 GHz. New York City: IEEE; 2019.

[13] Will C, Shi K, Schellenberger S, Steigleder T, Michler F, Fuchs J, et al. Radar-based heart sound detection. Sci Rep 2018;8(1):11551.

[14] Zhao H, Hong H, Sun L, Li Y, Li C, Zhu X. Noncontact physiological dynamics detection using low-power digital-IF Doppler radar. IEEE Trans Instrum Meas 2017;66(7):1780–8.

[15] Jiang X, Gao X, Wu X, Gu QJ, Liu X. Automatic RF leakage cancellation for improved remote vital sign detection using a low-IF dual-PLL radar system. IEEE Trans Microw Theory Tech 2023;71(6):2664–79.

[16] Li C, Lubecke VM, Boric-Lubecke O, Lin J. A review on recent advances in Doppler radar sensors for noncontact healthcare monitoring. IEEE Trans Microw Theory Tech 2013;61(5):2046–60.

[17] Shi K, Schellenberger S, Will C, Steigleder T, Michler F, Fuchs J, et al. A dataset of radar-recorded heart sounds and vital signs including synchronised reference sensor signals. Sci Data 2020;7(1):50.

[18] Wen L, Dong S, Wang Y, Gu C, Tang Z, Liu Z, et al. Noncontact infant apnea detection for hypoxia prevention with a K-band biomedical radar. IEEE Trans Biomed Eng 2024;71(3):1022–32.

[19] Wang W, Song R, Wu Y, Zheng L, Zhang W, Chen Z, et al. Deep learning-based automated diagnosis of obstructive sleep apnea and sleep stage classification in children using millimeter-wave radar and pulse oximeter. Sleep Health 2025;11(6):859–67.

[20] Li X, Duan B, Zhang Y, Guo Y. Optimal design of aperture illuminations for microwave power transmission with annular collection areas. Engineering 2023;30:63–74.

[21] Guo J, Shen Y, Dong G, Han Z, Hu S. A retrodirective array enabled by CMOS chips for two-way wireless communication with automatic beam tracking. Engineering 2024;37:196–207.

[22] Wen L, Cao J, Guo Y, Zeng Z, Cao Q, Chen K, et al. Robust and adaptive DC offset calibration in microwave sensing systems for long-term microwave cardiogram detection. IEEE Trans Microw Theory Tech 2026;74(2):1756–69.

[23] European Union. Regulation (EU) 2016/679 (General Data Protection Regulation), article 9: processing of special categories of personal data. Off J Eur Union 2016;L119:1–88.

[24] Bhutani S, Elgendi M, Menon C. Preserving privacy and video quality through remote physiological signal removal. Commun Eng 2025;4(1):66.

[25] Institute of Electrical and Electronics Engineers (IEEE). IEEE Std 802.11bf-2025: IEEE standard for information technology-telecommunications and information exchange between systems local and metropolitan area networks-specific requirements-part 11: wireless LAN MAC and PHY specifications-Amendment 4: enhancements for wireless LAN sensing. IEEE standard. New York City: IEEE; 2025.

[26] Du R, Hua H, Xie H, Song X, Lyu Z, Hu M, et al. An overview on IEEE 802.11bf: WLAN sensing. IEEE Commun Surv Tutor 2025;27(1):184–217.

[27] Zhao H, Hong H, Miao D, Li Y, Zhang H, Zhang Y, et al. A noncontact breathing disorder recognition system using 2.4-GHz digital-IF Do
Journal Pre-proofs

[28] Zhao B, Fu CH, Hong H, Shi L. Enhancing remote heart rate monitoring with FedQ²: focusing on motion interference in federated learning. IEEE Sens J 2025;25(20):39054–63.

[29] Eden R, Chukwudi I, Bain C, Barbieri S, Callaway L, de Jersey S, et al. A scoping review of the governance of federated learning in healthcare. NPJ Digit Med 2025;8(1):427.

[30] U.S. Food and Drug Administration. Cybersecurity in medical devices: quality management system considerations and content of premarket submissions. Guidance for Industry and Food and Drug Administration Staff. Silver Spring: US Food and Drug Administration; 2026.

[31] Yang S, Kernec JL, Romain O, Fioranelli F, Cadart P, Fix J, et al. The Human Activity Radar Challenge: benchmarking based on the radar signatures of human activities dataset from Glasgow University. IEEE J Biomed Health Inform 2023;27(4):1813–24.

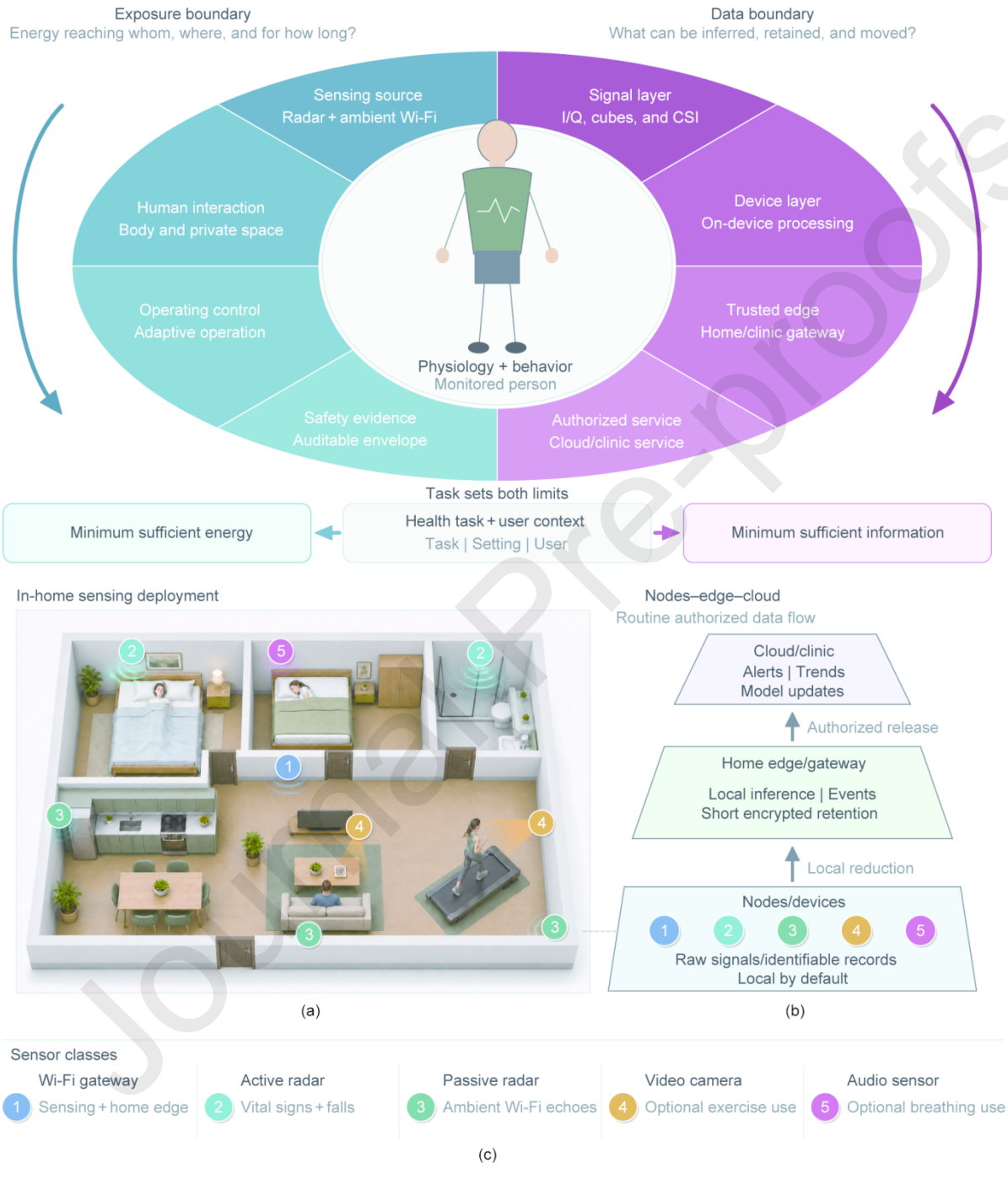
Journal Pre-proofs

Declaration of Interest Statement

☒ 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.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for this journal and was not involved in the editorial review or the decision to publish this article.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:



Journal Pre-proofs