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Toward ISAC-Inspired WiFi–Radar Fusion for Privacy-Preserving Elderly In-Home Monitoring

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Abstract. Population aging is increasing demand for unobtrusive in-home monitoring, while cameras raise privacy concerns, and wearables depend on user compliance. This critical survey and design study compares WiFi channel-state information sensing and millimeter-wave FMCW radar for fall detection, activity recognition, and vital-sign monitoring. It identifies cross-environment generalization, multi-occupant attribution, and privacy evaluation as key barriers to deployment. An ISAC-inspired architecture is proposed that combines broad, low-cost WiFi coverage with radar in high-risk areas and uses cross-modal consistency checking to detect modality-specific unreliability. A controlled synthetic simulation illustrates that this mechanism can prevent an unstable modality from degrading fusion under asymmetric domain shift, but does not establish real-world or clinical performance. The paper also distinguishes among visual, behavioral, and health data privacy and identifies priorities for synchronized datasets, cross-home evaluation, and privacy-aware alert governance.

Keywords: WiFi sensing, channel state information, millimeter-wave radar, integrated sensing and communication, fall detection, ambient assisted living, elderly care, privacy

1. Introduction

Population aging and the preference for aging in place are increasing demand for continuous, unobtrusive in-home monitoring, particularly for falls and functional decline [1]. Cameras can achieve strong recognition performance but raise privacy concerns in bedrooms and bathrooms, while wearable devices depend on being worn, charged, and tolerated at the moment of an event [2, 3].

RF sensing provides a non-visual, device-free alternative. WiFi channel-state information (CSI) reuses commodity 802.11 infrastructure for broad activity sensing, whereas millimeter-wave FMCW radar provides finer range, Doppler, and physiological measurements [4-6]. Neither modality records conventional images, but both can still reveal sensitive behavioral or health information.

WiFi and radar research have largely developed separately, leaving few synchronized datasets and limited guidance on complementary failure modes. This paper, therefore, compares the two modalities for elderly in-home monitoring, proposes an ISAC-inspired cooperative architecture with cross-modal consistency checking, illustrates the mechanism using synthetic simulation, and

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identifies deployment priorities for generalization, multi-occupant attribution, and privacy governance.

2. Related surveys and positioning of this work

Existing surveys separately cover WiFi-CSI sensing and cross-domain generalization [4, 7], mmWave human sensing and radar-based fall/activity recognition [6, 8, 9], multimodal fall detection [10, 11], and contactless vital-sign monitoring [12, 13]. Among the surveys reviewed, none jointly compares WiFi-CSI and mmWave radar for elderly in-home monitoring while also examining ISAC-inspired cooperation, privacy beyond image capture, and a concrete cross-modal reliability mechanism. This paper, therefore, integrates these previously separate strands within a narrower elder-care focus.

3. WiFi channel-state-information sensing

3.1. Sensing principle

Commodity WiFi devices operating under the IEEE 802.11n/ac/ax standards report channel state information for each subcarrier of an OFDM transmission as part of normal MIMO channel estimation [4]. CSI describes amplitude attenuation and phase shift along each multipath component between a transmitter and receiver antenna pair and is therefore sensitive to any change in the propagation environment, including human presence and motion [14-17]. Because the same physical-layer mechanism that enables communication produces this measurement, no additional hardware beyond a CSI-capable network interface card is required [4, 7]. The dominant sensing pipeline extracts amplitude and phase time series per subcarrier, applies noise reduction — commonly principal component analysis or wavelet-based denoising — and computes time-frequency representations, most often via the short-time Fourier transform, from which motion-discriminative features are derived [4, 7]. These features feed a classifier, historically support vector machines and more recently convolutional or recurrent neural networks, that maps a window of CSI activity to a discrete activity label [4].

3.2. Fall detection and activity recognition

FallDeFi used time-frequency CSI features selected for transfer across rooms and evaluated both single- and multi-occupant settings [18]. More recent deep models achieved 94.85% overall accuracy in controlled environments, but only a 60% fall-class true-positive rate when deployed in an unmodified hospital room without retraining [14]. Because these are different metrics, they should not be interpreted as a direct percentage-point decrease, but they show that strong laboratory performance did not translate into reliable field detection.

This limitation is consistent with Monjur et al., who reported 13–54% accuracy drops across unseen environments and 12–20% drops when only the occupant changed [15]. Together, these studies indicate that CSI classifiers often learn room-specific multipath signatures rather than motion alone, making cross-domain generalization a central barrier to deployment [7].

3.3. Limitations

Beyond cross-environment transfer, CSI has three further limitations. First, it aggregates the effects of multiple occupants, making individual attribution difficult [4, 7]. Second, commodity CSI offers

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lower physiological resolution than dedicated radar. Third, stable CSI access remains hardware- and firmware-dependent: performance can vary with chipset, packet rate, bandwidth, antenna configuration, placement, and room layout. Practical deployment, therefore, requires installation-specific calibration and monitoring of signal drift [4, 7, 14].

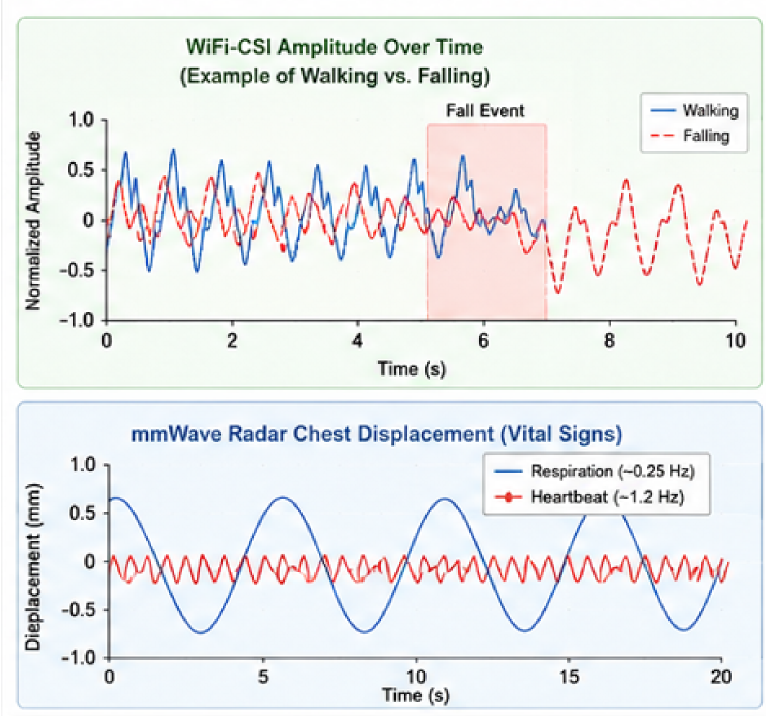

Figure 1. Example signal characteristics

4. Millimeter-wave FMCW radar sensing

4.1. Sensing principle

FMCW radar transmits a continuously frequency-swept chirp and mixes the received echo with the transmitted signal to produce an intermediate-frequency beat signal whose frequency is proportional to target range. In contrast, phase progression across successive chirps encodes velocity through the Doppler effect [5]. Operating in the 60–77 GHz band gives mmWave radar a wavelength of a few millimeters, allowing it to resolve sub-millimeter chest-wall displacement from heartbeat and the larger displacement from respiration as distinct, separable phase oscillations [12]. The same range-Doppler pipeline also produces micro-Doppler signatures that differ characteristically across gait, sitting, bending, and falling [5, 9].

4.2. Vital-sign monitoring

Contactless vital-sign monitoring is where mmWave radar offers the clearest advantage over WiFi-CSI, because sub-millimeter periodic chest-wall motion lies at or below the limit that CSI amplitude processing on commodity hardware can reliably recover [6, 12]. Raheel et al.'s survey identifies FMCW radar as a promising contactless option for vital-sign monitoring, particularly under controlled and relatively stationary conditions, while noting that heart-rate estimation remains sensitive to respiration harmonics, body motion, and signal quality [12]. Hassanpour and Yang argue

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that multi-task learning can exploit physiological dependencies among vital signs and may improve robustness relative to independently trained estimators [13], suggesting the heart-rate difficulty may be partly an artifact of problem framing rather than a fixed sensing limit.

4.3. Activity recognition and fall detection

The same processing pipeline supports fall recognition: a fall produces a rapid, high-velocity descent followed by an abrupt cessation, which is separable in the time-frequency domain from walking or sitting [5]. Hu et al.'s survey of 74 studies since 2000 finds that micro-Doppler analysis with classical classifiers has been dominant until a recent shift to deep architectures, paralleling the WiFi-CSI literature's own trajectory [8]. Ullmann et al., focusing on continuous rather than isolated recognition, identify activity segmentation as a persistent error source distinct from per-activity accuracy [9]. Diraco et al.'s UWB-radar system, evaluated with 30 participants, reports up to 95% accuracy discriminating dangerous situations from daily activities while explicitly engineering for non-visual privacy [2].

4.4. Limitations

Radar deployment is constrained by more than hardware cost. Performance depends on chirp configuration, antenna aperture, mounting height and angle, and the availability of a clear sensing region; furniture, walls, bedding, body orientation, and gross motion can attenuate or mask the small phase variations used for vital-sign estimation. Multiple people or pets may produce overlapping range–angle–Doppler signatures, and radar cannot always determine which household member generated an event without additional tracking or identification. Reproducibility is also affected by vendor-specific preprocessing and restricted access to raw signals. Finally, most studies use short, single-room trials, so long-term drift, installation sensitivity, and cross-home robustness remain insufficiently tested [6, 8, 9, 12].

5. Toward an isac-inspired cooperative sensing architecture

5.1. From strict ISAC to ISAC-inspired cooperative sensing

In this paper, ISAC is used as an architectural inspiration rather than as a claim that the proposed system already implements a single dual-functional waveform. Conventional multimodal fusion combines measurements or decisions from separate sensors after data acquisition. Strict ISAC, by contrast, integrates sensing and communication through shared waveforms, radio hardware, spectrum, or coordinated network resources [10, 11]. The proposed design lies between these categories: WiFi infrastructure provides both communication and CSI-based sensing. At the same time, a dedicated mmWave radar supplies complementary measurements, and the two streams are coordinated at the system level. It is therefore more precise to describe the architecture as ISAC-inspired cooperative sensing. Future 802.11bf-enabled devices could move the design closer to strict ISAC by making sensing a native network function rather than an opportunistic extraction process [16].

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5.2. A layered fusion architecture

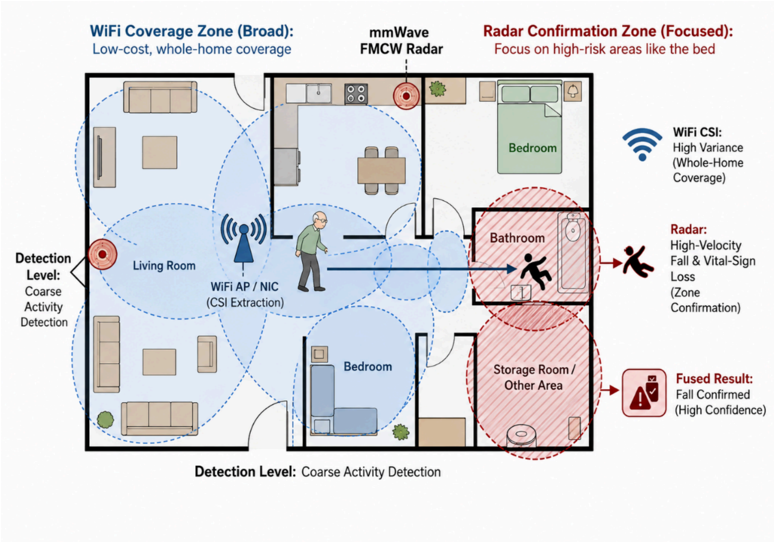

Figure 2. Deployment concept of WiFi–radar cooperative sensing for elderly in-home monitoring

Data-, feature-, and decision-level fusion are established strategies and are retained in Fig. 3 only as implementation options [3, 13]. The distinctive function proposed here is cross-modal consistency checking, which operates on temporally aligned outputs from the WiFi-CSI and radar branches. For each observation window, t, the two branches produce event probabilities $p_c(t)$ and $p_R(t)$, predicted activity labels $y_c(t)$ and $y_R(t)$, and modality-specific quality scores $q_c(t)$ and $q_R(t)$. A disagreement is recorded when the two branches predict different labels or when the absolute difference between their event probabilities exceeds a predefined margin, δ. Thus, disagreement refers to inconsistent event-level inference within the same synchronized time window, rather than a difference between their raw signal representations. These variables are introduced here to formalize the proposed architecture; the simplified simulation in Section VI does not implement the full quality-score model.

Reliability is then assessed separately for each modality. The CSI quality score may incorporate packet loss, amplitude and phase instability, deviation from the calibration distribution, and changes in hardware or transmitter–receiver placement. The radar quality score may incorporate signal-to-noise ratio, target-track continuity, range–angle ambiguity, occlusion, and contamination by gross body motion. When both modalities are reliable and agree, the fused event is accepted with high confidence. When only one modality satisfies its reliability threshold, the system follows the reliable branch. When both are reliable but disagree, the event is marked uncertain, and an additional observation window, sensing modality, or human confirmation is requested. When neither branch is reliable, the system abstains from issuing a high-confidence autonomous decision and reports the sensing failure explicitly.

This mechanism does not assume that radar is universally more trustworthy than CSI. The preferred modality depends on the observed quality indicators and the type of event. Radar may receive greater weight for vital-sign estimation or when CSI exhibits evidence of environmental shift. In contrast, CSI may remain useful for broad activity coverage when the radar target is occluded or outside its effective sensing region. The synthetic simulation in Section VI uses a deliberately simplified version of this mechanism in which the radar-like modality is assigned a

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smaller deployment shift. Radar is therefore preferred during large disagreements only within that simulated scenario, not as a universal system rule.

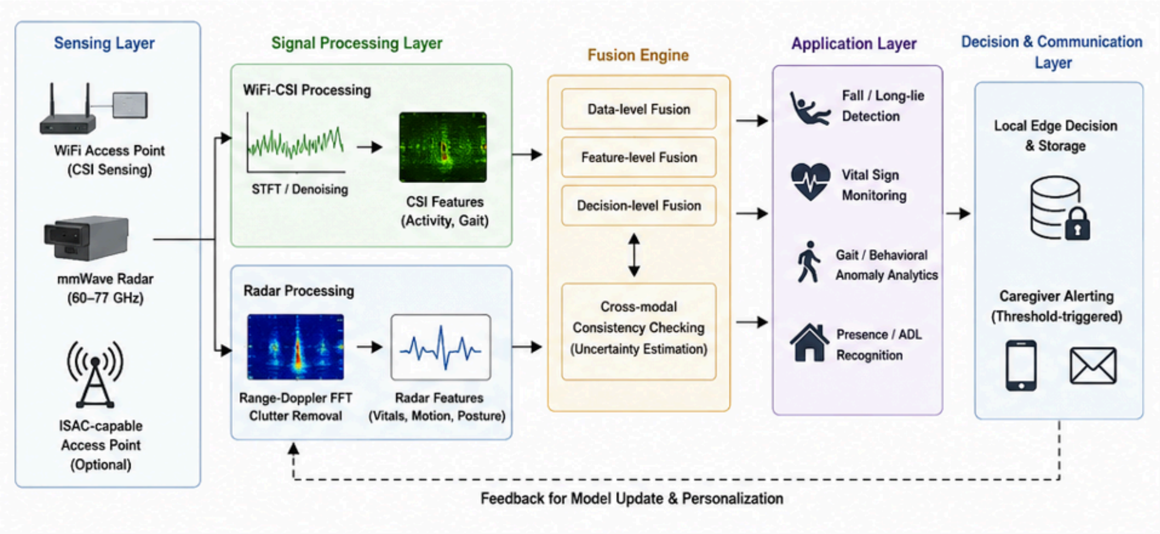

Figure 3. Layered fusion architecture for elderly in-home monitoring

5.3. Why fusion, not substitution

The case for combining rather than choosing between WiFi-CSI and mmWave radar follows from complementary failure modes, not a general intuition that more sensors are better. CSI sensing is inexpensive and already present in many homes, but it provides limited vital-sign resolution and generalizes poorly across environments [4, 7]. Radar provides finer vital-sign and gait measurements and may be less sensitive than CSI to some forms of multipath interference because it explicitly resolves range and Doppler. However, its robustness across homes, mounting configurations, and long-term deployments remains insufficiently validated, and dedicated radar hardware increases deployment cost [5, 6, 8, 9]. A decision that uses CSI for low-cost, whole-home coverage and radar, deployed in higher-risk zones such as bathrooms, for confirmation after a suspected event is implicit in several reviewed systems but rarely stated as an explicit principle [3].

6. Illustrative feasibility simulation

6.1. Motivation and scope

No reviewed study evaluates this consistency mechanism for the synchronization of WiFi-CSI and mmWave radar. A controlled synthetic simulation is therefore used only to illustrate its behavior under asymmetric cross-environment shift. The CSI-like modality is assigned a larger deployment shift than the radar-like modality, reflecting the stronger environment dependence reported for CSI [5-7, 15]. This is a modeling assumption rather than a physical measurement, and the simulation does not establish hardware, clinical, or real-world performance.

6.2. Simulation design

Each of the 200 independent repetitions generates 2,000 synthetic sensing events with a 10% fall prevalence, reflecting realistic class imbalance. A training environment gives each synthetic

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modality a clearly separable fall/non-fall signal. A held-out deployment environment then applies an environment-specific random shift. It adds noise to both modalities, calibrated so the CSI-like modality receives a substantially larger shift than the radar-like modality, consistent with the asymmetry argued above. Four strategies are evaluated on the deployment environment using thresholds fit only on the training environment, reproducing the train-in-lab, deploy-in-field condition documented empirically in [14] and [15]: CSI-only; radar-only; naive feature-level fusion (summed threshold-relative scores); and the proposed consistency-check fusion, which defers to the radar-only decision when the modalities disagree beyond a fixed margin and to the naive fused decision otherwise. Results are reported as mean ± SD across the 200 repetitions, as shown in Table 1.

Table 1. Comparison of simulation design and strategies

Strategy	Sensitivity (%)	False-Positive Rate (%)	F1 (%)
CSI-only	72.1 ± 19.3	27.4 ± 19.5	37.5 ± 7.8
Radar-only	86.4 ± 6.0	12.7 ± 5.5	58.6 ± 6.7
Naive fusion	84.7 ± 13.5	14.5 ± 12.6	58.2 ± 12.6
Proposed consistency-check fusion	86.4 ± 6.0	12.9 ± 5.4	58.4 ± 6.7

Values are reported as mean ± SD across 200 repetitions. The results are based on synthetic data rather than measurements from physical sensor hardware; see Section 6.2.

6.3. Results and limitations

Table I shows that CSI-only performance becomes both weaker and more variable under the assumed shift, whereas radar-only remains comparatively stable. Naive fusion recovers sensitivity but inherits part of CSI's variability. Consistency-check fusion achieves results nearly identical to radar-only, indicating that it prevents the unstable modality from degrading the fused decision rather than outperforming the best single modality.

This conclusion is limited to the specified asymmetric reliability assumption. Demonstrating synergy beyond the best modality would require recorded, time-synchronized WiFi-CSI and mmWave-radar data from the same events. The result should therefore be interpreted as an illustrative robustness floor, not evidence of universal radar superiority or real-world clinical effectiveness.

7. Privacy and ethical considerations

7.1. Visual privacy advantage

RF sensing reduces a specific category of privacy risk: the capture of conventional visual data. Unlike cameras, WiFi-CSI and radar do not directly record recognizable images of faces, bodies, clothing, or private domestic spaces. Their outputs cannot normally be reviewed as ordinary video footage, which may improve acceptability in sensitive areas such as bedrooms and bathrooms [2, 14]. This is a meaningful visual-privacy advantage, but it should not be treated as evidence that RF monitoring is privacy-neutral. The absence of images changes the type of sensitive information collected; it does not eliminate sensitive information.

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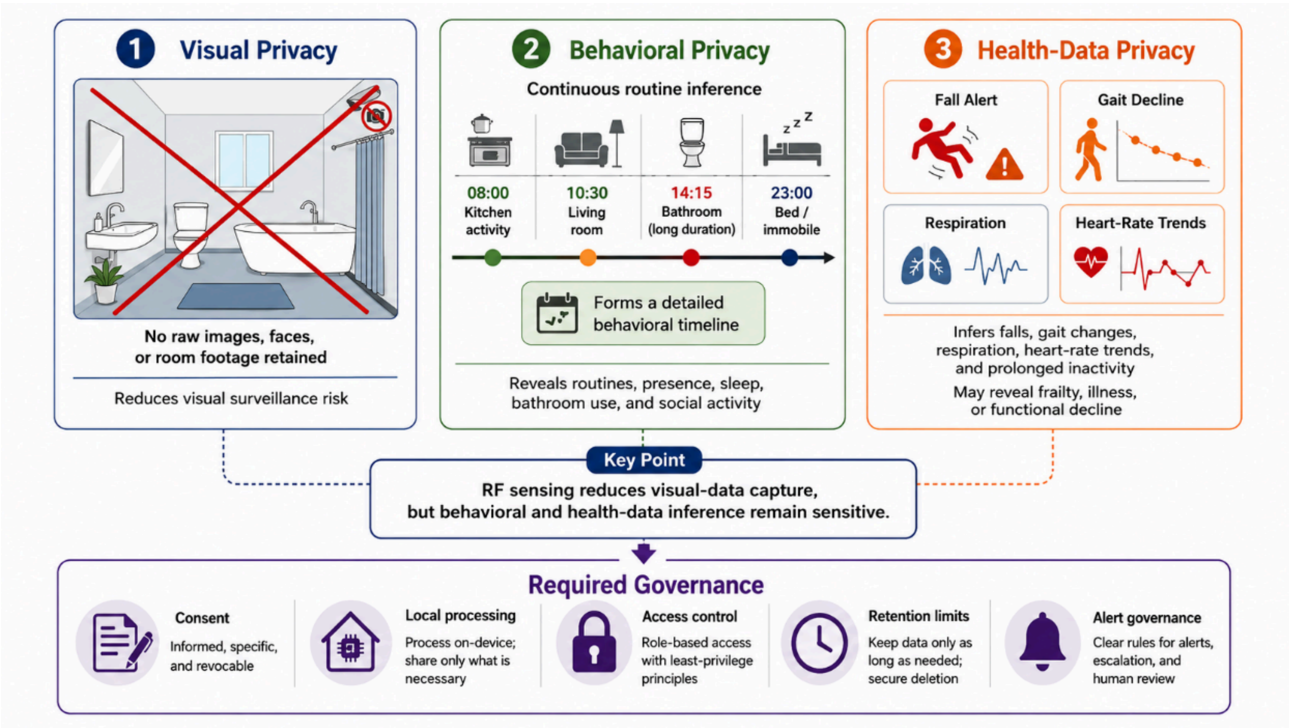

Figure 4. Visual, behavioral, and health-data privacy dimensions in RF-based elderly monitoring, together with the corresponding governance requirements

7.2. Behavioral and health-data risks

Visual privacy should be distinguished from behavioral privacy and health-data privacy. Behavioral data include room occupancy, sleeping and waking patterns, bathroom use, periods of immobility, social visits, and daily routines. Continuous RF monitoring can combine these observations into a detailed timeline of how a resident lives, even though no conventional image is retained. Unauthorized access or secondary use of such records could reveal when the resident is alone, how independently the person functions, or whether daily routines have changed [19].

Health-data risk arises when the same system infers falls, gait deterioration, respiratory rate, heart rate trends, or prolonged inactivity. These outputs may reveal frailty, illness, functional decline, or possible medical emergencies. They may therefore be sensitive not only to residents and caregivers but also in employment, insurance, institutional care, or legal contexts. Behavioral and physiological inferences should consequently be treated as sensitive data requiring purpose limitation, access control, retention limits, and explicit consent, rather than as harmless outputs merely because they are not images [19-21].

Privacy evaluation for RF monitoring should therefore address at least three dimensions: whether recognizable visual data are captured, what behavioral routines can be inferred, and what health conditions or functional changes can be derived. A system may perform well on visual privacy while still presenting substantial behavioral or health-data risks.

7.3. Governance, autonomy, and consent

These three privacy dimensions require different safeguards. Visual-data minimization depends primarily on avoiding raw imagery, whereas behavioral and health-data protection requires controls

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over inference, storage, access, sharing, and retention. Detailed RF-derived records should therefore remain local where possible, with caregiver-facing systems receiving only the minimum information required for a specific alert. Edge inference, access control, encrypted storage, federated model updates, and limited retention periods can reduce exposure, although technical protection does not replace meaningful consent [19-21]. Monitoring may be installed by adult children, caregivers, or institutions, so consent should be ongoing and revocable rather than treated as one-time proxy approval. Residents should be able to see when sensing is active, pause it, define private zones or time windows, and review who receives alerts. Systems should also distinguish clinical support from surveillance and document responsibility for false positives, missed falls, and delayed responses. Because no detector is infallible, alerts should be framed as decision support, with escalation paths and human review proportionate to the level of risk.

8. Comparative analysis and research priorities

8.1. Cross-modality comparison

Fig. 5 synthesizes the qualitative trade-offs documented across the reviewed literature for five in-home sensing modalities. WiFi-CSI and UWB radar both score highly on visual privacy because they do not directly capture conventional imagery, although Section 7 shows that behavioral and health-data risks remain. They also impose little wearable burden, supporting comparatively high user compliance [2, 4]. mmWave radar trades some through-wall capability relative to UWB for substantially higher vital-sign granularity [5, 6]. RGB/depth cameras, despite an advantage in multi-person discrimination and per-unit cost, are the only modality scoring at the floor on privacy preservation — the dimension motivating this paper's focus on RF alternatives [3]. Wearables present the converse profile: strong on most dimensions but weakest on user compliance, the specific failure mode that motivated RF-sensing research [3].

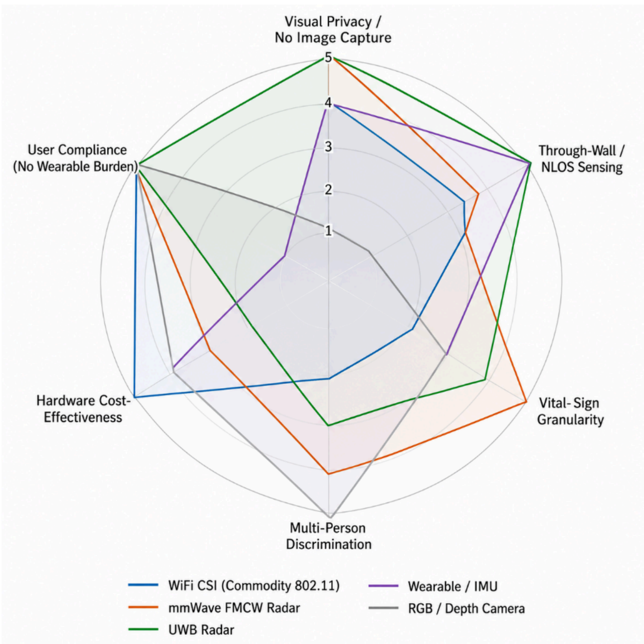

Figure 5. Qualitative comparison of in-home sensing modalities, synthesized from consensus across reviewed literature [2, 3, 4, 8]. Scale: 1 (low) to 5 (high)

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8.2. Research priorities

Four priorities follow from the preceding analysis. First, cross-home evaluation should become standard, with training and testing separated by environment, occupant, and hardware configuration. Recent work on WiFi-sensing generalizability further identifies domain adaptation, self-supervised learning, and standardized cross-domain benchmarks as important directions for reducing dependence on individual rooms, occupants, and hardware configurations [22]. Second, synchronized WiFi–radar datasets should include older participants, realistic long-term activities, and clinically meaningful definitions of fall. Evidence from other fall-detection modalities demonstrates why this requirement matters. A wearable system evaluated using genuine, unanticipated falls among older adults achieved lower real-world sensitivity than is commonly reported on simulated fall datasets [23]. In contrast, a vision-based study reported substantial performance degradation when a model trained on simulated falls was evaluated on unseen subjects [24]. Although these findings were not obtained using WiFi-CSI or radar, they indicate that the simulation-to-reality gap is a broader dataset and evaluation problem rather than a limitation unique to one sensing modality.

Third, multi-occupant and pet interference should be treated as a default deployment condition rather than an optional stress test. As illustrated in Fig. 6, WiFi-CSI combines the propagation effects of all occupants within the sensing area, making individual attribution difficult. At the same time, radar can separate targets through range, angle, and Doppler information, but may still fail when their signatures overlap [4, 6, 7, 9].

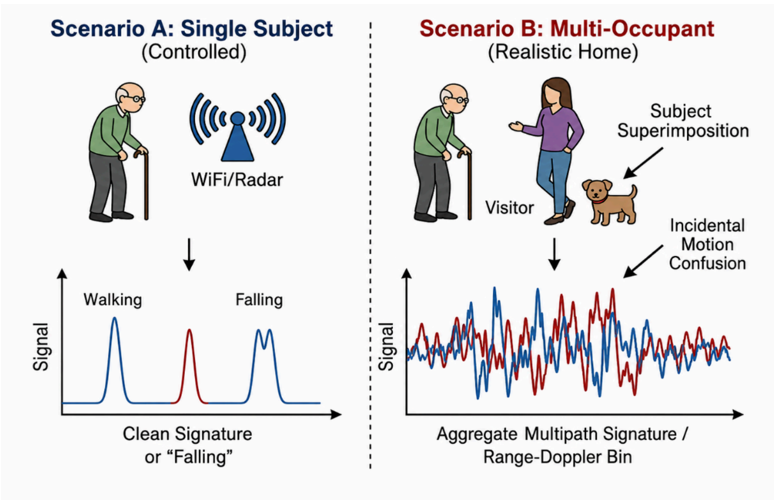

Figure 6. The multi-occupant separation challenge

Future benchmarks should therefore include spouses, caregivers, visitors, and pets, and should evaluate not only activity classification but also whether the system correctly attributes an event to the relevant individual. Fourth, privacy evaluation should measure behavioral and health data exposure, consent, data retention, and alert governance, in addition to the absence of images. Together, these priorities are more important to deployment readiness than further gains in accuracy on small, single-room benchmarks.

9. Conclusion

This paper has presented a critical survey and design study of WiFi radar sensing for elderly in-home monitoring. The review indicates that WiFi-CSI offers low-cost and potentially broad coverage but remains highly dependent on environment, hardware, and occupant conditions. In contrast, mmWave radar provides finer spatial and physiological information at a greater cost and with additional installation constraints. Based on these complementary characteristics, the paper proposed an ISAC-inspired cooperative sensing architecture centered on cross-modal consistency checking. The synthetic simulation showed only that, under the assumed asymmetric domain shift, the consistency rule can prevent an unstable modality from degrading the fused output; it did not demonstrate real-world synergy, hardware feasibility, or clinical effectiveness. The most important next steps are synchronized WiFi–radar datasets, cross-home and multi-occupant evaluation, explicit uncertainty calibration, and privacy governance covering behavioral and health-data inference as well as image capture.

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