

Non-intrusive Human Pose Sensing: A Comparative Review of Wi-Fi, Radar, and Inertial Sensing

Dongqi Cui *

Glasgow College of University of Electronic Science and Technology of China, Chengdu, China

* Corresponding Author Email: 2022190506017@std.uestc.edu.cn

Abstract. Non-intrusive human sensing has gained rapid momentum across smart homes, rehabilitation, safety monitoring and other applications. However, heterogeneous evaluation practices hinder fair cross-technology comparison. Thus, this paper focuses on three representative technologies—wearable sensors, radar sensing, and Wi-Fi sensing and consolidates reported findings onto a unified six-dimensional scheme: Accuracy, Response Speed, Cost, Privacy, Convenience, and Coverage. Those heterogeneous metrics are qualitatively mapped to high, medium, Low and visualized with radar charts. Based on these diagrams, this paper introduces a scenario requirement versus technology performance overlap procedure for scenario selection: the preferred option minimizes performance waste relative to the scenario's needs while satisfying all critical-dimension requirements. An example of industrial robot collision detection demonstrates the workflow's practicality and reusability. The paper also discusses limitations of the review methodology and future improvements, such as developing decision-making software. In conclusion, this paper provides a structured and actionable path for qualitative benchmarking and scenario-driven technology selection in non-intrusive human sensing.

Keywords: Non-intrusive human sensing; Wi-Fi sensing; Radar; Wearable sensors; Qualitative benchmarking.

1. Introduction

Non-intrusive human sensing is increasingly deployed across smart homes, rehabilitation, safety monitoring, and human-robot collaboration, enabling capabilities from continuous health tracking to device-free presence and behavior recognition [1-6]. Recent work has converted into three main lines of inquiry: wearable sensors—on-body or patch devices that capture human signals, widely used for fall detection and rehabilitation [1] [2]. radar sensing—UWB/mmWave reflections for contactless measurement, prominent in vital-sign and indoor monitoring [3] [4], and Wi-Fi sensing—CSI-driven, non-visual methods for presence, gesture, and coarse pose estimation [5] [6]. Despite pursuing similar goals, reporting and evaluation practices remain heterogeneous; the same task is measured under different metrics and thresholds, which undermines practical cross-technology comparison. For pose and key point estimation, Wi-Fi studies often report PCK@5/10 or MPJPE with inconsistent thresholding, radar papers report MPJPE or PCK under varied spatial criteria (e.g., 20 cm/50 px), and wearable studies frequently use AUC/MAE for classification or regression outcomes [7-11].

To address this gap, this paper surveys wearable, radar, and Wi-Fi sensing under a unified six-dimension scheme—Accuracy, Response Speed, Cost, Privacy, Convenience, and Coverage—and qualitatively maps heterogeneous metrics to high, Medium, Low, which are visualized via radar charts for intuitive comparison. Building on the unified representation, this paper adopts a concise selection routine: encode a scenario as a requirement radar, overlay it with each technology's performance radar, ensure that all critical axes are met, and then choose the option with the least performance waste. A case on industrial robot collision detection illustrates the workflow's practicality and reusability.

This paper has 3 main contributions: First, a unified qualitative benchmark aligning cross-paper metrics on six dimensions with visualization, second, a scenario-driven overlap criterion that selects methods by meeting critical dimensions with minimal waste, and third, a reusable paradigm

(industrial-robot case) showing an end-to-end path from requirement modeling to technology matching. Organization. Section 2 outlines mechanisms and modern applications of the three technologies. Section 3 reports six-dimension qualitative ratings and the overlap-based selection with the industrial-robot example. Section 4 discusses limitations and future development directions [1]-[11].

2. Technology Overview

2.1. Wearable Sensors

2.1.1. Development trajectory.

Wearable sensing began with accelerometers and gyroscopes for basic activity recognition and fall detection, evolved into multi-sensor IMUs, and recently expanded to flexible patches or e-skins that emphasize comfort and long-term adherence [1]. With low-power MCUs, Bluetooth, and edge inference, end-to-end pipeline data capture, on-device inference, and alerting and localization have become practical, with on-device inference and gateway-assisted localization demonstrated in engineering deployments [2]. Overall, the trajectory has converted from single-sensor, offline to “multi-modal fusion, online monitoring, and clinical or home use [1] [2].

2.1.2. Working principles.

Typical stacks include tri-axial accelerometers and gyroscopes such as optionally magnetometers, sensor fusion algorithms that provide orientation and kinematics, followed by feature extraction and learning-based inference (SVM/RF or sequence deep models such as LSTM/CNN/Transformer) for posture estimation, fall detection, and activity recognition [1]. Inference may run on-device for low latency and privacy or be offloaded to edge/cloud via a gateway for alerting or localization [2]. In terms of reporting, wearable studies frequently use AUC, MAE, and classification accuracy as primary metrics [11].

2.1.3. Modern applications.

Representative deployments include fall detection for seniors with real-time alerting in home and care facilities, postoperative rehabilitation and physical therapy support, where motion quality and adherence are quantified for individualized plans, and daily activity/posture tracking for longitudinal home health management. These settings prioritize long-term wearability, low power consumption, and minimal lifestyle disruption [1] [2].

2.1.4. Advantages and disadvantages.

Direct on-body sensing yields strong accuracy and responsiveness for individual users, on-device inference supports low latency and privacy, flexible, miniaturized form factors improve comfort and long-term adherence [1][2].

Coverage is inherently limited to the wearer, making multi-person and large-area monitoring nontrivial. Adherence and maintenance (charging, replacement, placement) affect long-term stability, device management and cost increase with scale, several tasks remain sensitive to mounting location and calibration [1][11].

2.2. Radar Sensing

2.2.1. Development trajectory.

Radar-based human sensing has evolved from long-range target detection to short-range, high-resolution indoor applications. UWB pulse systems offer fine-grained time-of-arrival resolution for vital signs and micro-motions, whereas mmWave FMCW systems leverage large bandwidth and MIMO arrays for joint range–Doppler–angle estimation and multi-target separation [3], [4]. Recent

studies progress from single-subject vital signs/presence to multi-target localization and tracking, including robustness under occlusion and through-obstacle conditions [3], [4].

2.2.2. Working principles.

A typical pipeline transmits a modulated waveform (UWB pulses or mmWave FMCW), performs dechirping or sampling, and applies time–frequency processing (FFTs/STFT) to form range–Doppler maps or point-cloud/voxel representations. Beamforming/MIMO DOA then provides angular estimates and target separation, followed by detection–association–tracking (e.g., Kalman/JPDA), or direct deep learning for motion/pose semantics [3]. Vital signs are derived from fine phase/amplitude perturbations with filtering and harmonic modeling [4]. For human pose and key points, radar studies commonly report MPJPE or thresholded PCK, with thresholds varying by dataset and task (centimeters/pixels/angle bins) [9]. [10].

2.2.3. Modern applications.

Representative deployments include contactless vital-sign monitoring in isolation wards, where micro-motions from respiration and heartbeat are tracked to enable continuous observation with low exposure risk [3], disaster search-and-rescue in collapsed structures, where UWB bio-radar leverages through-obstacle capability to detect life signatures and assist localization [4], and operation in strong-magnetic or vision-degraded environments (e.g., MRI suites, smoke/darkness), providing presence and motion/displacement sensing for safety monitoring and coordination [3] [4].

2.2.4. Advantages and disadvantages.

Contactless operation insensitive to lighting and visibility, through-obstacle sensing under specific materials/layouts [4], fast response enabled by high-rate sampling and on-device processing, MIMO/beamforming facilitates multi-target separation and angular estimation, supporting indoor localization with vital-sign monitoring [3].

Limited fine-grained pose and key point fidelity due to resolution and indoor multipath/occlusion, sensitivity to antenna placement and calibration, non-uniform metrics and protocols (MPJPE vs. PCK with varied thresholds) hinder cross-paper comparison, compared with infrastructure-reuse approaches, hardware and maintenance introduce additional costs [3], [4].

2.3. Wi-Fi Sensing

2.3.1. Development trajectory.

Wi-Fi sensing began with RSSI-based presence/motion detection and, with the adoption of 802.11n/ac/ax, shifted to CSI, which exposes subcarrier-wise, MIMO-aware channel responses. CSI enables fine-grained modeling of human-induced multipath, micro-motions, and gestures, combined with deep learning and domain adaptation, studies progressed from single-link setups to multi-AP/multi-link cooperation and from single-scene tuning to cross-scene generalization [5][6]. More recently, tasks have extended from presence/gestures to coarse pose and keypoints, positioning Wi-Fi sensing as a non-visual counterpart to vision/radar pipelines [5] [6].

2.3.2. Working principles.

Access points/NICs collect CSI $H(f, t)$ in amplitude and phase. Phase sanitization, CFO/clock-drift compensation, denoising, and subcarrier selection are applied before feature extraction (time/frequency, time–frequency/Doppler). CNN/LSTM/Transformer models then support presence detection, gesture recognition, and coarse pose regression [5][6]. Reporting varies by task: PCK at thresholds and MPJPE for pose/keypoints, and accuracy/F1/AUC for gestures/presence [5-8]. To mitigate domain shifts across rooms/devices, studies employ transfer/domain adaptation and multi-AP configurations [5] [6].

2.3.3. Modern applications.

Representative deployments include device-free presence and gesture control in smart homes, improving convenience and privacy by avoiding wearables and cameras [5] [6], anomaly/occupancy monitoring in apartments and hotel rooms for security patrols and service responses and, people counting/space occupancy in campuses and buildings to inform energy optimization and safety operations [5] [6]. These use cases leverage existing Wi-Fi infrastructure with minimal retrofitting and non-visual robustness to lighting.

2.3.4. Advantages and disadvantages.

Advantages: Reuses existing Wi-Fi infrastructure with low deployment/maintenance cost, contactless, non-visual, device-free operation supports privacy, multi-AP/MIMO layouts enable wider coverage and multi-person sensing, rapid in-situ deployment integrates well with home/office networks [5] [6].

Disadvantages: Sensitive to multipath and environment shifts, cross-room/device domain gaps reduce generalization, dependence on NIC drivers/sampling and vendor heterogeneity complicates reproducibility, higher-level tasks (e.g., pose) remain affected by metric/threshold choices (PCK vs. MPJPE), requiring unified mapping for fair comparison [5-8].

3. Qualitative Performance and Matching Workflow

3.1. Qualitative Mapping and Visualization

3.1.1. Purpose and stance.

This subsection establishes a shared qualitative vocabulary over Accuracy, Response Speed, Cost, Privacy, Convenience, and Coverage, using high, medium, and low as ordinal tags for cross-technology comparison and visualization. The method follows three principles, the first is narrative synthesis, decisions reflect expert judgment on reported trends without fixed cutoffs or claims of statistical significance, the second principle is conservative merging, when findings are mixed or strongly context dependent prefer the middle level and state boundary conditions, the last principle is direction harmonization, invert error and expenditure measures to a higher is better interpretation before assigning qualitative levels.

3.1.2. Three level mapping rules.

The tiers are conceptual, not numeric cutoffs: High denotes stable and consistent strength under typical settings, medium denotes outcomes that vary with scene or thresholds, and low denotes frequently reported limitations. Dimension reading follows three points: judging Accuracy and Response Speed from task narratives and comparative trends with robustness across scenes and multi person settings, reading Cost, Privacy, Convenience, Coverage from infrastructure and operations burden, identifiability and wear requirements, installation and maintenance effort, and propagation plus topology for space and multi person capability, and handling uncertainty conservatively, when evidence conflicts or domain gaps appear or an outlier exists prefer Medium and state assumptions and scope.

3.1.3. Visualization specification with example.

For clear communication, results are visualized with radar charts, as is demonstrated in Figure.1. The specification consists of three points, the chart encodes maps High, Medium, Low to 3, 2, 1, and the axes use a fixed order of Accuracy, Response Speed, Cost, Privacy, Convenience, and Coverage and remain consistent across the paper, and a style draws one chart per technology while requirement and performance radars share the same axes and ticks for direct overlays later, Figure.1 illustrates the example style.

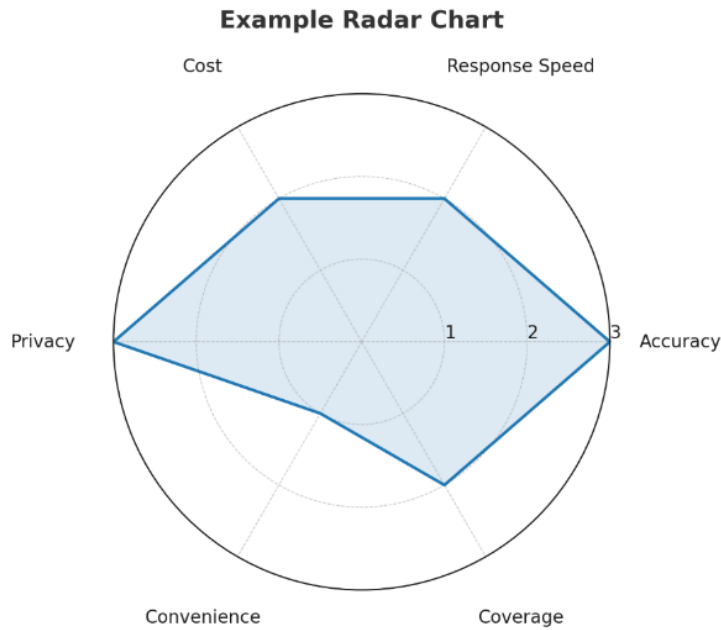


Figure 1. Example radar chart

3.2. Consolidated qualitative ratings

Wearable, on-body signals enable strong recognition and fast on-device response, at scale adherence and maintenance introduce management overhead, so Cost and Convenience are medium, Coverage is limited to the wearer, so low, Privacy is favorable without environmental imaging yet involves individual physiological data and consent, so medium [1] [2] [11].

Radar, UWB and mmWave provide high-rate sampling with local processing so Response Speed is high, macro activities and vital signs are robust while fine pose is affected by resolution and multipath so Accuracy is medium, deployment and calibration keep Cost and Convenience at medium, typical room scale coverage is medium, privacy is generally friendly without imaging while through-obstacle capability requires compliance boundaries so medium [3] [4] [9] [10].

Wi-Fi, existing infrastructure lowers deployment and maintenance burden, so Cost and Convenience are high. Non-visual and device-free operation supports Privacy at high levels. Multi-AP topologies enable broader space and multi-person sensing, so Coverage is high, accuracy, and response are influenced by multipath and domain shifts when generalizing across scenes, so both are medium [5-8].

Table 1 presents conceptual tiers for wearable, radar, and Wi-Fi sensing across six dimensions, using high, medium, and low for subsequent matching and visualization.

Table 1. 6-dimensional evaluation of 3 technologies

Technology	Accuracy	Response Speed	Cost	Privacy	Convenience	Coverage
Wearable	High	High	Medium	Medium	Medium	Low
Radar	Medium	High	Medium	Medium	Medium	Medium
Wi-Fi	Medium	Medium	High	High	High	High

These are qualitative tiers, not numeric cutoffs, meaning 3 levels: High denotes stable and consistent strength under typical settings, medium denotes context or threshold dependent outcomes, and low denotes frequently reported limitations. The assignments follow Section 3.1, using conservative merging and triangulated evidence.

3.3. Scenario Requirement Modeling

To connect task needs with technology assessment, scenario requirements are mapped to the same six dimensions and three levels used in Section 3.2. The process follows three steps. First is defining critical dimensions and the minimum acceptable levels, for safety-critical tasks Accuracy and Response Speed are typically critical, second is assigning high, medium, low to each of the six dimensions based on task goals, risk tolerance, budget, and environment, third is generating a requirement radar that shares axes and encoding with the performance radars so that overlays are straightforward

For alignment with requirement radars, the three technology performance radars are demonstrated in Figure 2, Figure 3 and Figure 4, using high=3, medium=2, low=1 with axes ordered as Accuracy, Response Speed, Cost, Privacy, Convenience, Coverage.

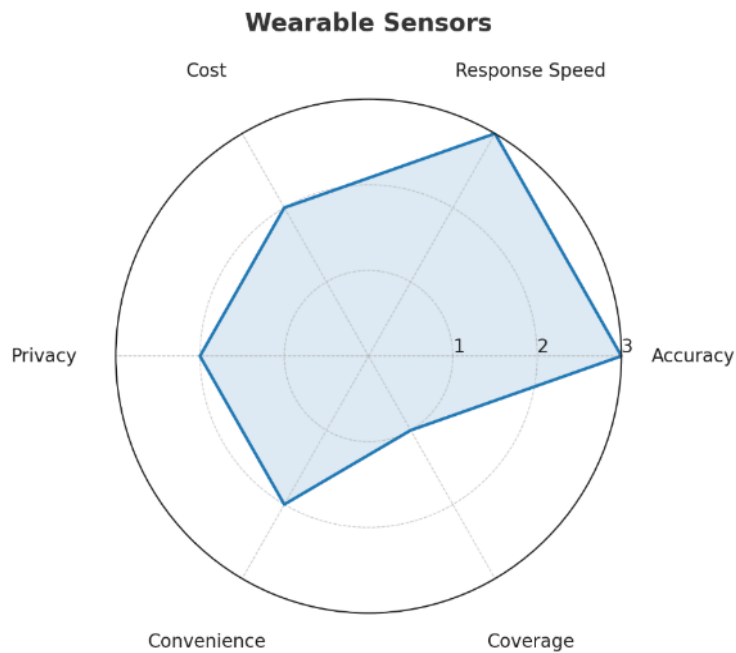


Figure 2. Performance radar of Wearable Sensors

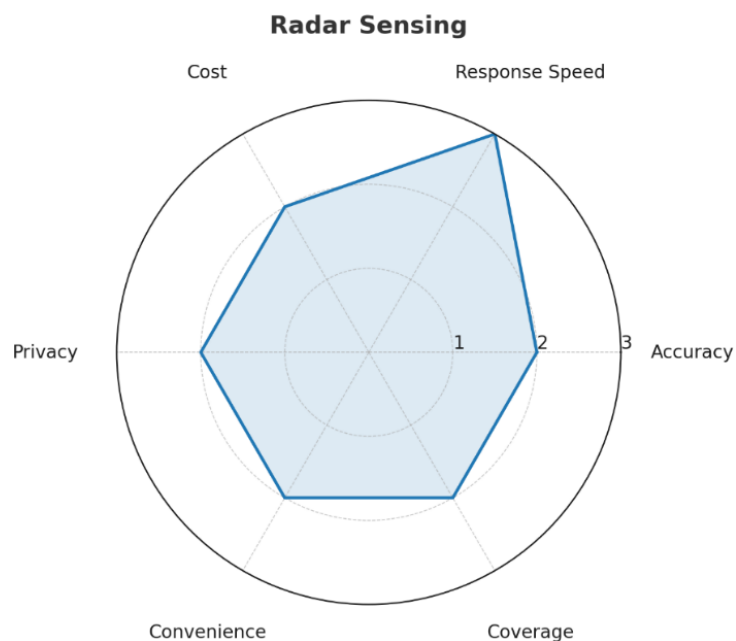


Figure 3. Performance radar of Radar Sensing

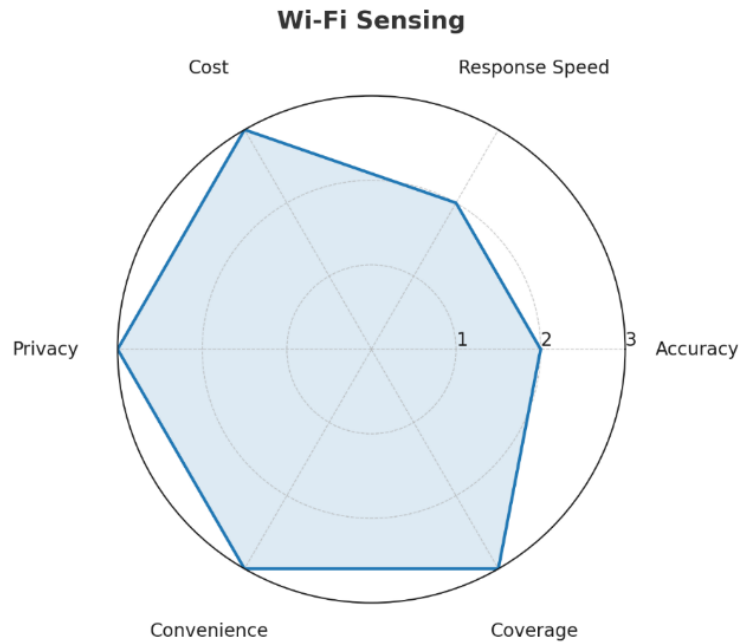


Figure 4. Performance radar of Wi-Fi Sensing

3.4. Matching Criterion and Workflow

3.4.1. Selection criterion.

On the same six dimensional axes, the decision follows three rules, the first rule is critical axes first, any candidate must meet or exceed the required level on declared critical dimensions, otherwise it is discarded, the second is overlap have the second priority, among feasible candidates prefer the one with larger overlap with the requirement radar, meaning more dimensions satisfied with closer fit, the third is to have minimal waste, when overlap is similar prefer the option with less redundancy on non-critical axes to reduce cost and complexity.

3.4.2. Workflow.

Encode high, medium, low as 3, 2, 1 for rule execution and proceed in four steps, first, inputs and tags, provide the requirement vector r and each technology vector t , mark the set of critical axes C , second, feasibility filter, for each candidate check all c in C that $t[c] \geq r[c]$, otherwise remove, third, overlap and waste, for remaining candidates compute S as the number of axes with $t[d] \geq r[d]$ or an equivalent closeness measure, and compute W as the sum of positive surplus $\max(t[d] - r[d], 0)$, fourth, ranking and rationale, sort by higher S then by lower W , if still tied choose the option with simpler deployment and maintenance and provide an explicit rationale and mitigation for any shortfall.

3.4.3. Visualization and decision presentation.

Overlay the requirement radar with each candidate's performance radar, use distinct colors and annotate S and W in the title so reviewers can see which axes are satisfied and where surplus or gaps remain. For unsatisfied critical axes, propose two remedies, one is parametric adjustments, for example, increasing node counts or optimizing placement to improve coverage or accuracy; the other is hybrid deployment, when two technologies complement different axes and the budget allows, add a minimal secondary layer to satisfy the specific constraint.

3.4.4. Tie-breaking and hybrid rules.

When candidates are nearly identical in S and W apply three preferences: choose the option with less retrofit, choose the one with clearer compliance boundaries to reduce privacy and regulatory overhead, and if a single solution is marginal on a critical axis adopt a lightweight hybrid that only addresses that axis rather than full stacking.

3.4.5. Deliverables.

The final output should include three items, the selected technology with its overlay chart, a short table of critical axis satisfaction and remaining waste, and if gaps exist a minimal cost engineering remediation list with milestones for implementation and review.

3.5. Case Study: Industrial Robot Collision Detection

3.5.1. Scenario and critical axes.

A fenced and interlocked robot cell runs cyclic pick and place or assembly, with metal racks and conveyors nearby, lighting and dust vary by shifts, human proximity is frequent. The policy requires immediate reaction to approach or trespass without changing workers' wearing or routines. Visitors and shift rotations make wearables risky, cameras face occlusion, glare, and privacy constraints, the scope is a single cell and its entrances. The three-level requirement is $r = [Accuracy=3, Response\ Speed=3, Cost=2, Privacy=2, Convenience=3, Coverage=2]$.

Response Speed and Coverage are critical, with a wearing device free preference.

3.5.2. Requirement radar chart.

Figure 5 shows the requirement radar chart with the same axes.

Requirement Radar — Industrial Robot Collision Detection

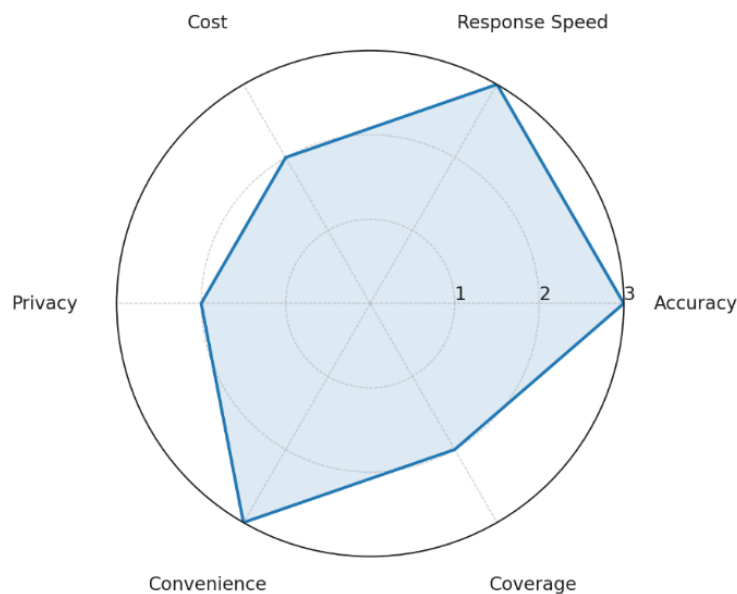


Figure 5. Requirement radar chart for industrial robot collision detection case

3.5.3. Overlap overview and three overlays.

Radar satisfies both critical axes, Wearable misses Coverage, Wi-Fi misses Response Speed. Overlays are demonstrated in Figure 6, Figure 7 and Figure 8.

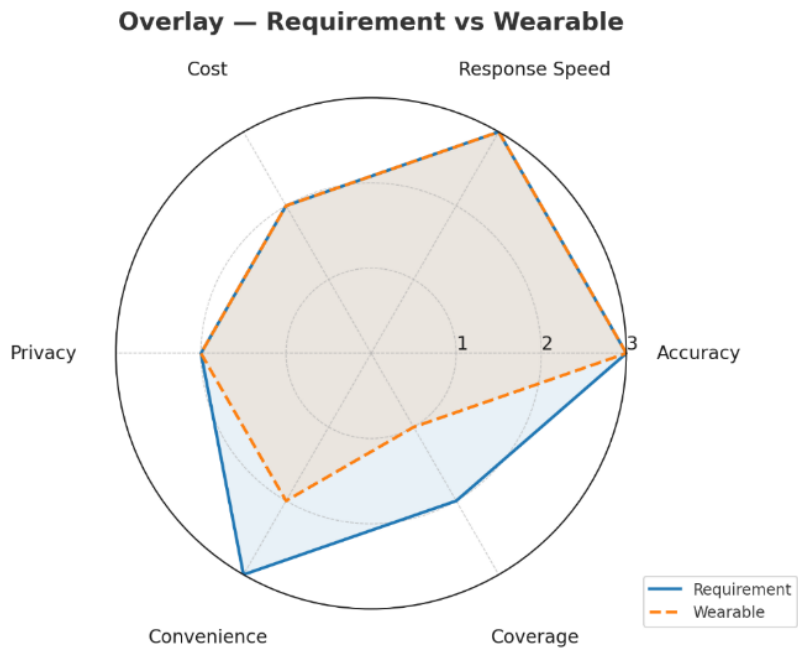


Figure 6. Overlay of requirement vs wearable sensors

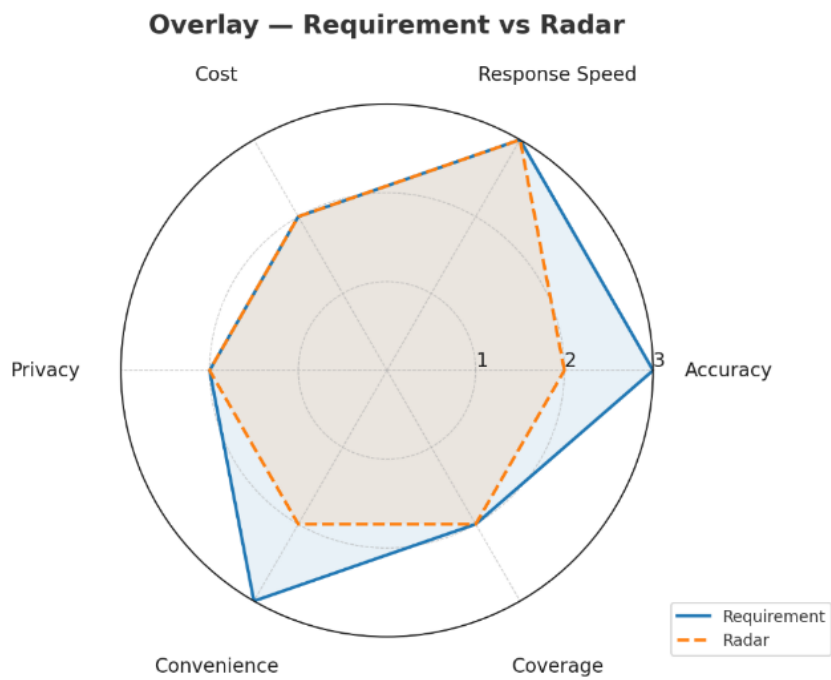


Figure 7. Overlay of requirement vs radar sensing

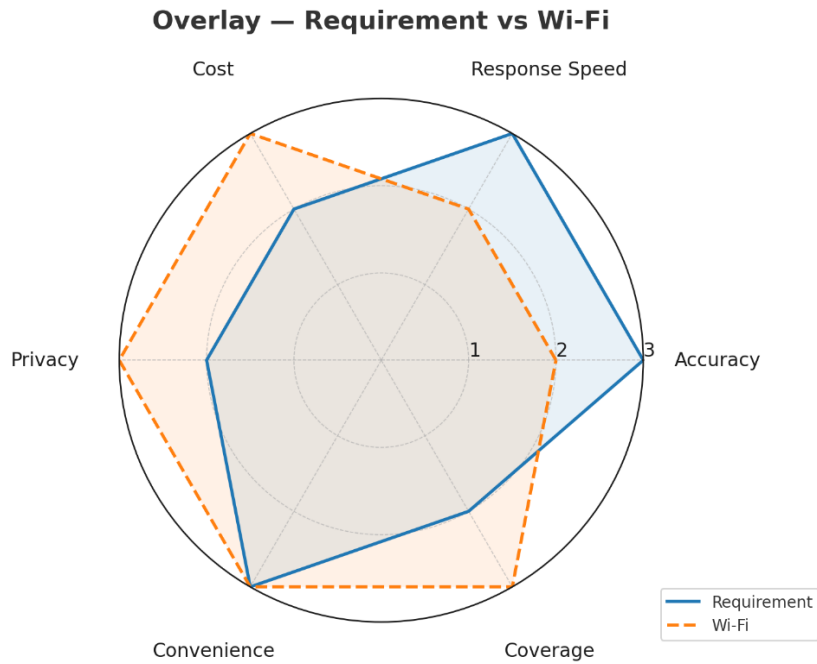


Figure 8. Overlay of requirement vs Wi-Fi sensing

3.5.4. Best option under the workflow.

Using Section 3.4, Wearable is infeasible due to Coverage $1 < 2$, Wi-Fi is infeasible due to Response Speed $2 < 3$, Radar meets both critical axes, achieves $S=4$ satisfied axes with $W=0W=0W=0$ surplus, therefore feasible and preferred. It is device free, integrates with safety interlocks, reacts quickly, and covers room scale entrances and boundaries. In conclusion, the best option is selected as the radar sensing.

4. Conclusion

This paper unifies three representative paradigms of nonintrusive human sensing, wearable, radar, and Wi-Fi, under a six-dimensional qualitative scheme and a general selection routine. The contributions are: a shared qualitative vocabulary over Accuracy, Response Speed, Cost, Privacy, Convenience, Coverage with radar chart visualization to compare capability contours across papers and technologies, a requirement versus performance overlay criterion that first enforces critical axes then selects the feasible option with larger overlap and smaller redundancy, and an end-to-end industrial robot collision detection case that demonstrates practicality and reusability.

The proposed methodology is qualitative and evidence informed, which implies several limitations, the first limitation is subjective tiering, the boundary between high and medium relies on expert reading and narrative synthesis rather than testable cutoffs, the second limitation is context dependence, protocols and environments vary across studies so cross paper consistency is limited and conclusions should be interpreted directionally, the third limitation is evidence coverage, the corpus cannot be exhaustive and some axes may be conservative due to task or material bias, and the last is the visual interpretation, radar charts serve communication and comparison, they do not imply statistical significance and should not be used for linear arithmetic.

Future work targets the review and selection methodology rather than improving any single sensing algorithm, with four priorities, the first is corpus expansion and standardization pipeline, continuously ingest recent studies and maintain a reusable alignment workflow including direction harmonization and conservative aggregation, the second is sensitivity and uncertainty analysis, perturb expert weights and scenario settings to report stability ranges and conservative recommendations, the third is scenario library and decision tool, encapsulate frequent scenarios into reusable requirement templates and build a lightweight tool for requirement entry, radar overlays, feasible set ranking, and

report export, last is to provide reproducible assets, open source scripts, figure styles, and table schemas so others can replay the tiering and selection and update results as new evidence arrives.

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