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From Laboratory Prototype to Sustainable Deployment: Smart Garment Technologies for Construction Safety Monitoring and a Multidimensional Readiness Framework

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Abstract

Construction workers face disproportionate rates of fatal and nonfatal injuries, including falls, heat strain, overexertion, and struck-by incidents, that passive personal protective equipment cannot continuously monitor. Smart garments, which embed sensors and microelectronics directly into textile apparel, offer a deployable infrastructure for continuous worker-level physiological and kinematic monitoring. This PRISMA-guided systematic review synthesizes 76 records (search executed 31 December 2025; coverage 2000–2026), of which 63 are empirically validated and used for benchmarking. Four analytical contributions are made: (i) a tiered corpus classification separating construction-direct, transferable, and contextual evidence; (ii) stratification of all performance claims by validation context; (iii) explicit transferability assessment for records from healthcare, occupational safety, sports, and rehabilitation; and (iv) a deployment-maturity framework evaluating readiness across technical performance, validation maturity, operational durability, human and organizational acceptance, and system integration, extending beyond single-dimension scores such as NASA TRL. Only 7 of 63 empirical records (11%) were field or field-simulated, of which 6 reached TRL 5; most other systems remain at TRL 4. The framework suggests that technical performance is less often the primary limiting dimension than validation maturity, durability, and integration, although this conclusion is constrained by the dominance of laboratory and transferable evidence.

Keywords: smart garments; wearable sensors; construction safety; systematic review; technology readiness level; deployment readiness; sustainable occupational health

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1. Introduction

The construction industry is increasingly instrumented by digital technologies, yet occupational injury and fatality rates remain high despite regulatory oversight, safety training, and widespread use of conventional personal protective equipment [1]. Research output on smart sensing for construction safety has grown substantially over the past two decades [2]. Construction worker fatalities and injuries impose cascading sustainability costs: direct costs include medical treatment, compensation, and project delay, while indirect costs include productivity losses, workforce attrition, and long-term disability that undermine the

social and economic dimensions of sustainable development. Incidents associated with the "Fatal Four", falls, struck-by, electrocution, and caught-in-between, remain dominant, indicating that traditional hazard-control strategies relying on administrative controls, passive PPE, and post-event reporting must be complemented by information technology that continuously senses and communicates evolving site risks. Sustainable construction, as defined under the United Nations 2030 Agenda and specifically Sustainable Development Goal 8 (Decent Work and Economic Growth), requires not only environmental and economic performance but the protection of workers' health and physical wellbeing as a foundational condition. Because risk evolves through interactions among workers, equipment, and environment, precursors such as fatigue, heat strain, and unsafe posture often develop within a work shift but are rarely monitored continuously, limiting proactive intervention. Framed as a prevention tool, smart-garment monitoring functions as a leading-indicator safety control that can trigger timely work–rest adjustments, hazard-zone avoidance, and supervisory response before near-misses escalate into recordable injuries [3].

Advances in sensing technologies, embedded systems, wireless communication, and data analytics have driven a shift toward automation-enabled safety management. Early wearable systems, including wrist-worn, clip-on, and helmet-mounted devices, demonstrated feasibility for monitoring movement and physiological signals [4,5], yet deployment revealed limitations such as unstable sensor placement, limited sensing bandwidth, battery constraints, worker discomfort, and PPE incompatibility. These challenges accelerated development of sensor-integrated smart garments, including instrumented shirts and vests embedding biosensors [5,6], Inertial Measurement Units (IMUs), environmental sensors, and communication modules, into work apparel. By enabling stable, multimodal monitoring with minimal workflow disruption, smart garments can function as distributed sensing nodes within safety management platforms [7,8].

Despite growing research interest, the literature remains fragmented. Studies differ widely in sensing architecture, analytical methods, performance metrics, and validation environments, limiting cross-study comparison and understanding of technological readiness and scalability [1,9]. Existing reviews often aggregate wearables across industries or focus on single hazards, underrepresenting construction-specific constraints [9–11] related to data acquisition architectures, wireless connectivity, integration with site information systems, and deployment feasibility. Table 1 summarizes key gaps, including inconsistent benchmarking, limited field validation, unclear technology readiness, weak system integration, and underreported deployment barriers.

Table 1. Structured research gaps in smart garment development for construction safety.

Dimension	Current State in Literature	Identified Gap	Implication for Field
Performance metrics	Heterogeneous reporting (accuracy, F1, sensitivity inconsistently defined)	Lack of standardized benchmarking frameworks	Cross-study comparison remains methodologically constrained
Validation context	Predominantly laboratory-based studies	Limited longitudinal field validation	Limited empirical evidence of real-world robustness
Technology readiness	Prototype-level systems	Absence of explicit TRL classification	Uncertainty regarding deployment maturity

Table 1. *Cont.*

Dimension	Current State in Literature	Identified Gap	Implication for Field
System integration	Rare integration with site-level management systems	Limited BIM/digital twin connectivity	Constrained positioning within broader construction automation ecosystems
Deployment barriers	Underreported ergonomic and data governance considerations	Limited assessment of adoption feasibility	Potential barriers to industry-scale implementation

Prior wearable reviews in construction [9–11] identified fragmentation in the literature but did not make four distinctions that are central to evaluating deployment readiness. First, prior reviews did not separate construction-direct evidence from transferable evidence from adjacent domains, meaning that performance claims could not be contextualized against the type of evidence supporting them. Second, prior reviews did not stratify performance claims by validation context, meaning that laboratory results were implicitly treated as operational benchmarks. Third, prior reviews did not assess transferability of smart-garment evidence from healthcare, sports, and occupational safety to construction with explicit scope criteria. Fourth, no prior review proposed a multidimensional readiness framework that distinguishes between prototype performance limitations and field-deployment limitations across governance, durability, and integration dimensions. This review addresses these gaps through four analytical contributions: (i) a tiered corpus classification that separates 18 construction-direct or -adjacent records, 45 transferable records, and 13 contextual sources; (ii) systematic stratification of all performance claims by validation context, revealing that high-performance figures in the literature are predominantly laboratory results; (iii) explicit transferability assessment for non-construction records; and (iv) a deployment-maturity framework that evaluates construction readiness across five dimensions, technical performance, validation maturity, operational durability, human and organizational acceptance, and system integration, and identifies the specific dimension limiting deployment for each system type.

This review addresses four research questions. This article is positioned as a diagnostic systematic review: rather than proposing a new sensor architecture or theory from scratch, it maps the existing evidence base, diagnoses deployment-readiness gaps, and identifies which dimensions currently prevent smart garments from moving from prototype validation to operational construction safety use.

RQ1: How has the smart-garment evidence base evolved across developmental waves?
RQ2: How does validation context shape reported performance across hazard domains?
RQ3: What deployment barriers are consistent across the three corpus tiers?
RQ4: How does the deployment-maturity framework distinguish systems approaching operational readiness from those remaining at prototype stage?

2. Background

2.1. Smart Garments as Distributed Cyber–Physical Sensing Systems

Smart garments embed sensors directly into clothing, enabling continuous monitoring of workers' physiological and physical conditions [9]. Sensor-integrated smart garments can be viewed as distributed cyber–physical sensing nodes embedded at the human–construction interface. Unlike external wearables, these systems integrate sensing, signal conditioning, processing, and communication directly into textile substrates. Typical architectures include textile-embedded sensors, conductive pathways, microcontroller units, wireless communication modules, and external analytics platforms [7,8]. Data

pipelines generally progress from physiological, kinematic, or environmental signal capture to filtering, feature extraction, machine learning inference, and transmission of alerts or decision-support outputs. In construction environments, this pipeline must operate under vibration, temperature variation, perspiration, dust exposure, and intermittent connectivity, imposing strict requirements on durability, signal stability, latency, and energy efficiency.

Within construction informatics, the discipline concerned with the design, implementation, and evaluation of information systems for the built environment [12], smart garments function as data acquisition nodes whose value is realized through integration with project management platforms, digital twins, and safety monitoring dashboards, not through standalone device operation. Worker-level data streams generated by garments can be fused with positioning systems, equipment monitoring feeds, and site dashboards, and interfaced with BIM models and construction digital twins [13–15], positioning smart garments as edge sensing nodes where raw signals are transformed into safety-relevant information objects. Figure 1 shows the layered cyber–physical architecture of this sensor-integrated system.

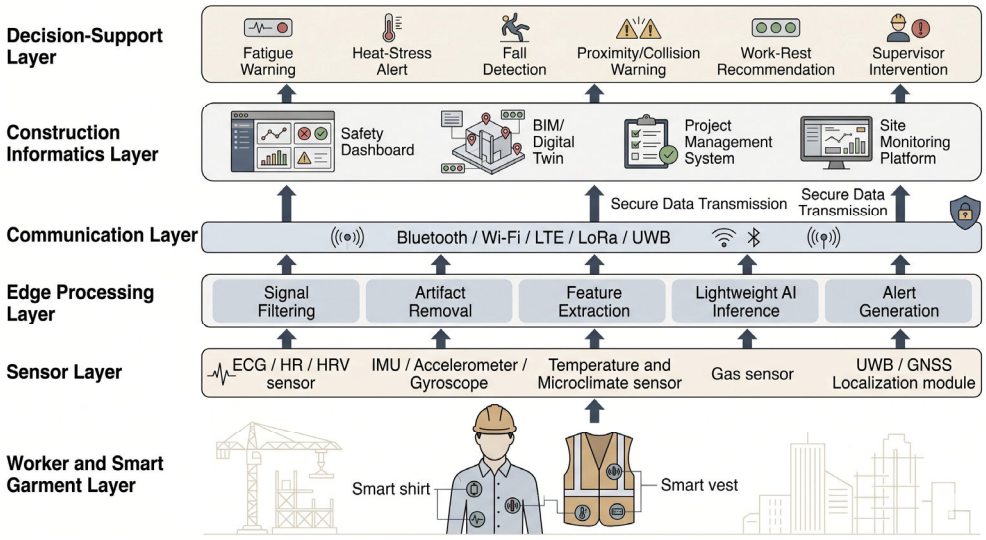


Figure 1. Layered cyber–physical architecture of sensor-integrated smart garments for construction safety.

Construction differs from healthcare, sports, and other domains from which most transferable smart-garment evidence in this corpus is drawn in ways that directly affect deployment feasibility. Construction workers have no fixed workstation and move continuously across changing, often outdoor, task zones, unlike clinical or laboratory settings where sensing infrastructure is co-located with the patient or athlete. Personal protective equipment is already mandatory on most sites, so a smart garment must integrate with, rather than replace or compete with, existing PPE such as hard hats, harnesses, and high-visibility apparel. Environmental exposure, dust, vibration, heat, moisture, and abrasion from tools and materials, is more severe and more variable than in clinical or athletic-performance settings, imposing durability and washability demands that most corpus records do not test.

Construction workforces also have comparatively high turnover and frequently include subcontracted or transient labor, which complicates device provisioning, fit, and long-term data continuity. Finally, unlike a hospital or a sports-training facility, most construction sites lack a centralized IT infrastructure to manage, charge, and maintain wearable devices at scale, so any deployment must function with minimal site-level technical support. These differences mean that performance and durability findings from healthcare or sports contexts cannot be assumed to transfer directly to construction deployment, which is one

reason this review evaluates transferable evidence separately from construction-direct evidence throughout.

2.2. Signal Processing and Artificial Intelligence Foundations

Raw signals from textile sensors require preprocessing, including filtering, artifact removal, and feature extraction, prior to inference [16]. Common modeling approaches include support vector machines, random forests, k-nearest neighbors, convolutional neural networks, and recurrent architectures such as LSTM [17–19]. Model selection depends on signal complexity, computational limits, and latency requirements; embedded inference favors lightweight models that can run on garment-level microcontrollers, whereas cloud or edge servers support more complex architectures and facilitate integration with construction data platforms, albeit with additional communication delays.

A recurring limitation is limited model generalizability [16]. Many studies rely on small, homogeneous samples under laboratory conditions, while construction environments involve significant worker and site variability. Without cross-population or field validation, reported performance may overestimate real-world effectiveness, underscoring the importance of domain adaptation, cross-site validation, and IT-focused evaluation protocols that reflect how models will operate within live construction information systems.

2.3. Sensing Modalities and Textile Integration Challenges

Smart garments typically integrate physiological, kinematic, and environmental sensing [16,17,20]. Physiological monitoring (e.g., ECG, respiration, skin temperature, EMG) faces challenges related to consistent skin contact, motion artifacts, and conductivity changes caused by perspiration and garment deformation. Kinematic sensing using IMUs and accelerometers enables posture and fall detection but is sensitive to drift, sensor displacement, and non-linear worker motion. Environmental sensing introduces trade-offs between exposure accuracy and protection against mechanical damage. Across modalities, washability, mechanical stress, long-term conductivity, and ergonomic compatibility remain central constraints [21–23], highlighting that sensing feasibility depends equally on material resilience, user comfort, and the ability to maintain reliable data streams into construction monitoring and analytics platforms.

2.4. Validation Contexts and Technological Readiness

Validation practices range from laboratory experiments and pilot trials to limited field studies [9,10]. Laboratory validation offers control but lacks ecological realism; pilot studies provide partial realism with limited statistical power; field testing introduces operational complexity but improves applicability. Technological readiness levels (TRLs) are used in this review as an operational classification to distinguish laboratory feasibility, controlled prototype validation, and pilot or field validation. In construction contexts, readiness depends not only on sensing accuracy but also on durability, energy autonomy, user acceptance, data security, and integration with management workflows. Inconsistent maturity reporting across studies obscures the gap between experimental performance and deployable capability, particularly when smart garments are expected to function as persistent nodes in distributed construction IT infrastructures.

2.5. Integration and Deployment Considerations in Construction Environments

Transitioning from prototype systems to operational deployment requires addressing systemic and human-centered constraints. Energy management, durability under mechanical stress, compatibility with PPE, and worker comfort directly influence adoption [3,24,25]. Integration with existing site management platforms, safety reporting systems, and data governance requirements is essential for scalability [1,26]. Cybersecurity considerations,

including encryption, anonymization, and access control, are also critical when transmitting physiological or location data.

These technical and organizational factors determine whether smart garments can function as deployable elements of construction safety management systems. From a sustainability perspective, each of these constraints carries additional significance [21–23]: energy inefficiency accelerates battery consumption and electronic waste; poor durability shortens garment lifespan and increases material throughput; and inadequate data governance undermines worker trust and may disproportionately affect vulnerable or low-income construction workers, raising social equity concerns. Evaluating deployment readiness therefore encompasses not only technical performance but the environmental, economic, and social dimensions of sustainability [3,25] that determine whether these systems can be adopted at scale without introducing new sustainability trade-offs.

2.6. Benchmarking and Reporting Inconsistencies

Cross-study synthesis is hindered by inconsistent performance metrics and reporting practices [9,24]. Studies vary in definitions of accuracy, sensitivity, and false alarms, with many omitting confusion matrices or contextual evaluation details. Limited dataset transparency and variation in sampling protocols further reduce reproducibility and comparability. Standardized reporting, including dataset characteristics, validation strategies, and environmental context, is necessary [22,24] to support reliable benchmarking and meaningful assessment of technological progress.

3. Methodology

3.1. Research Design and Protocol

This study was conducted as a systematic review to synthesize and critically evaluate empirical research on sensor-integrated smart garments developed for construction safety applications. The review protocol was designed in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement and predefined before full-text screening to support methodological transparency and limit post hoc analytical modification. A completed PRISMA 2020 checklist is provided within Supplementary File S1. The review protocol was retrospectively registered on OSF Registries after completion of the review for transparency and reproducibility. The registration DOI is https://doi.org/10.17605/OSF.IO/V27RS. This document predefined the search strategy, inclusion and exclusion criteria, data extraction framework, quality appraisal rubric, technological readiness scoring procedure, and statistical synthesis plan. The unit of analysis was the peer-reviewed publication. Where the same research group published a conference paper and a journal paper using the same dataset or system, only the more complete journal version was retained for benchmarking to avoid double-counting.

Because directly construction-relevant smart-garment evidence is limited, and only 18 of 76 retrieved records involve construction workers, construction sites, or construction-equivalent validated tasks, this review adopts an explicitly tiered scope. Three evidence categories are distinguished throughout: (1) core/adjacent construction evidence: garment-integrated studies in which participants were construction workers or performed validated construction-equivalent tasks; (2) transferable evidence: garment-integrated studies from healthcare, sports, occupational safety, and rehabilitation in which the garment architecture, sensing modality, or validation approach applies directly to construction worker monitoring; and (3) contextual sources: review papers, broader wearable studies, and conceptual articles used for background framing only. This classification is operationalized in the Corpus Role column of Supplementary File S1, Sheet S2. All quantitative benchmarking in the Results section draws only from records in categories 1 and 2 (63 empirical records).

Contextual sources are cited for framing in the Background and Discussion sections but do not contribute to any performance statistic, quality score, or deployment-maturity assessment. The deliberate exclusion of standalone wearables (wristbands, smartwatches, helmet-only sensors) was imposed to maintain conceptual homogeneity in system architecture and deployment characteristics. Garment-integrated systems exhibit distinct ergonomic, signal stability, power management, and PPE-compatibility properties that differ fundamentally from externally attached devices; combining these categories would introduce heterogeneity that compromises benchmarking validity.

The temporal boundary was defined from 1 January 2000 through 31 December 2025 (search execution date), with one early-access publication dated 2026 included as described in Section 3.2. The year 2000 was selected to reflect the beginning of widespread miniaturized embedded sensing and wireless communication technologies compatible with smart textile integration. The effective coverage range of the corpus is 2000–2026.

3.2. Information Sources and Search Strategy

A structured database search was conducted following PRISMA 2020 guidance to identify peer-reviewed literature on smart garments for construction safety. The search was executed on 31 December 2025 in Scopus, Web of Science Core Collection, and IEEE Xplore, selected to provide complementary coverage across engineering, computer science, and construction management domains.

Searches were limited to English-language journal articles and indexed conference proceedings published between 2000 and 2025, with one formally dated 2026 early-access article retained because it was retrievable at the 31 December 2025 search date. The English-language restriction was applied to ensure interpretative consistency during full-text extraction and to reflect resource feasibility for dual-reviewer assessment. This restriction is a potential source of geographic coverage bias; studies published in other languages may include relevant systems not captured here. The three databases searched provide substantial English-indexed content from non-Anglophone research communities, partly mitigating this concern. Field restrictions were applied to Title–Abstract–Keyword (or the nearest equivalent indexing fields) to improve precision.

The following Boolean search strategy was used in Scopus syntax:

TITLE-ABS-KEY
(“smart garment*” OR “smart vest*” OR “smart shirt*” OR “e-textile*” OR “textile-integrated sensor*” OR “garment-embedded sensor*” OR “smart PPE”)
AND
(“construction worker*” OR “construction site*” OR “construction safety”)
AND
(“fatigue detection” OR “heat stress” OR “ergonomic risk” OR “fall detection” OR “collision avoidance” OR “proximity warning” OR “physiological monitoring” OR “biomechanical monitoring”).

Database-specific search strings for Scopus, Web of Science Core Collection, and IEEE Xplore are provided in Supplementary File S1, Sheet S5 to enable exact replication, including field-specific tag syntax, the seed set of 35 known relevant publications used for recall verification, and the search execution date. The search string was designed to maximize precision for construction-context records; it was pilot-tested against the seed set prior to final execution to verify recall adequacy. Because this precision-focused string would not retrieve transferable records from adjacent domains (healthcare, sports, occupational safety), which do not contain construction-specific terminology, those records were identified through a structured supplementary process described below.

No additional database searches were performed after 31 December 2025; the 2026-dated early-access article was already retrievable during the original search. The initial

search returned 742 records (Scopus: 328; Web of Science: 276; IEEE Xplore: 138). After duplicate removal, 601 unique records remained for screening.

Because the primary database search was designed to maximize precision for construction-context records, transferable records from adjacent domains (healthcare, occupational safety, sports, rehabilitation) were identified through a structured supplementary process: (i) backward citation screening of all construction-direct records retrieved in the primary search; (ii) forward citation screening using Web of Science; and (iii) review of the predefined seed set. This supplementary process is documented separately from the primary search pathway in the PRISMA flow diagram (Figure 2) and in Supplementary File S1, Sheet S5. Transferable records identified through this process were subject to the same PICOS eligibility assessment and the four-criterion transferability rubric described in Section 3.4. These records were retained only when at least two of the following four transferability criteria were met, as assessed independently by two reviewers: (i) garment architecture comparable to construction PPE in terms of form factor and sensor placement; (ii) sensing modality directly applicable to a construction hazard domain (ergonomic, thermal, cardiovascular, or fall); (iii) validation protocol involving physical tasks with biomechanical demands comparable to construction work; or (iv) deployment barrier (durability, power, governance) directly relevant to construction site conditions. Records meeting only one criterion were excluded. Transferable records are classified separately in Supplementary File S1, Sheet S2 under the Corpus Role column and were not treated as direct construction evidence. Pathway-specific counts for supplementary citation screening were reconstructed from the screening log and seed-set audit and are reported in Supplementary File S1, Sheet S5. Because backward citation, forward citation, and seed-set records were not independently logged as separate PRISMA pathways during the original search, these values should be interpreted as best-estimate disaggregation rather than independently tracked pathway counts.

One publication in the final corpus carries a formal publication date of 2026: Edirisinghe and Gunathilake [27], published in *Engineering, Construction and Architectural Management* as an early-access article (DOI: 10.1108/ECAM-06-2024-0813). This article was retrievable and fully accessible at the 31 December 2025 search date and satisfied all PICOS eligibility criteria on dual-reviewer full-text assessment. It is included as a standard corpus member and classified as core/adjacent construction smart-garment evidence in Supplementary File S1, Sheet S2. The effective coverage range of the corpus is therefore 2000–2026. Transferability criteria were applied using the following four-criterion decision framework. A record was retained as transferable only when at least two of the four criteria were met by independent reviewer assessment; borderline cases were resolved through consensus discussion, with a third reviewer serving as adjudicator when needed: (T1) comparable garment architecture: the garment form factor and sensor placement must be comparable to construction PPE or workwear (e.g., smart vest, shirt, or harness compatible with construction apparel); (T2) construction-relevant sensing modality: the sensor modality must directly map to a construction safety hazard (e.g., IMU for posture/fall detection; ECG/HRV for fatigue monitoring; skin temperature for heat stress; UWB/GPS for localization); (T3) construction-equivalent task demand: validation tasks must involve physical demands comparable to construction work (e.g., repetitive lifting $\geq$10 kg, sustained overhead reaching, kneeling, bending, scaffold climbing, or manual material handling); (T4) deployment-barrier relevance: the study must report barriers directly relevant to construction deployment (e.g., durability, washability, power autonomy, PPE compatibility, worker comfort, data governance). Criteria met by each transferable record are documented in the T1–T4 columns of Supplementary File S1, Sheet S2.

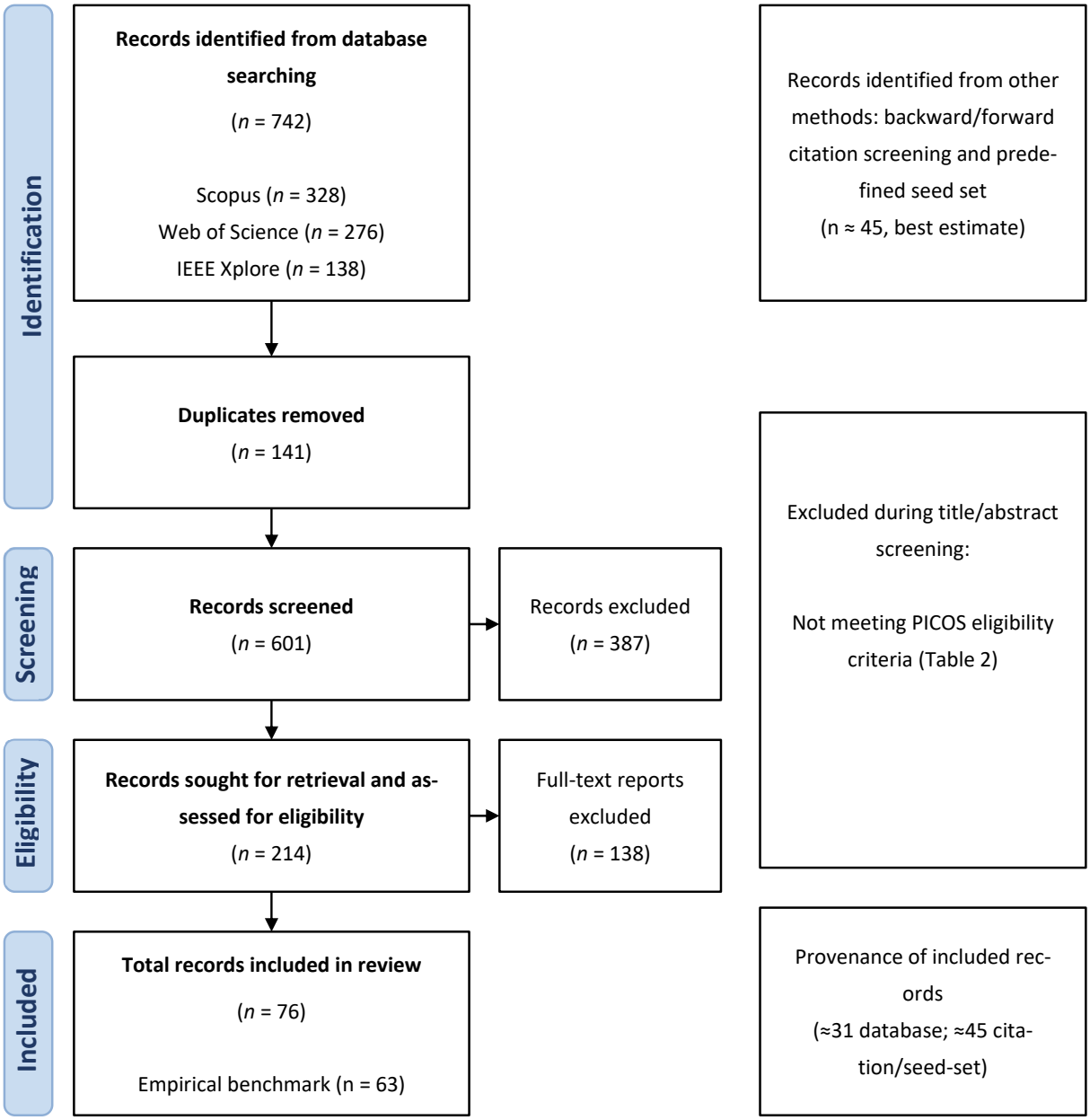


Figure 2. PRISMA 2020 flow diagram for study identification, screening, eligibility assessment, and inclusion, showing both identification pathways, database searching (n = 742: Scopus, Web of Science, IEEE Xplore) and other methods, backward/forward citation screening and a predefined 35-record seed set ($n \approx 45$, best estimate). The inclusion stage shows: 76 total records included in the review (best-estimate provenance ≈ 31 via database searching, ≈45 via citation screening/seed-set expansion); 63 empirical benchmark records used for quality scoring, TRL classification, and performance synthesis; and 13 contextual/broader records used for background and framing only. Pathway-specific sub-stage counts for the other-methods route were not independently logged; disaggregation estimates and the reconstructed seed list are provided in Supplementary File S1, Sheet S5.

3.3. Study Selection and Screening Procedure

All retrieved records were exported to EndNote (Version 21) for automated duplicate detection followed by manual verification. Screening was conducted using Rayyan (Version 3.0), which supports blinded independent review. Two reviewers independently screened titles and abstracts for relevance based on predefined eligibility criteria. Inter-rater

agreement was calculated on a randomly selected 25% subsample (n = 150) using Cohen's kappa coefficient:

Observed agreement (P_o) was 0.91, with $\kappa = 0.86$, indicating substantial agreement based on established interpretation thresholds ($\kappa \geq 0.80$). Disagreements were resolved through a structured adjudication protocol involving independent re-evaluation and written justification exchange; unresolved cases were decided by a third reviewer.

Disagreement counts were recorded during dual-reviewer screening but are not retained in the final submission dataset. The structured adjudication protocol, independent re-evaluation followed by written justification exchange, with unresolved cases decided by a third reviewer, is described above. The kappa coefficient ($\kappa = 0.86$) was calculated on the randomly selected 25% subsample and reflects agreement achieved prior to adjudication.

After title and abstract screening, 214 articles proceeded to full-text review. Of these, 138 were excluded for the following reasons: non-garment wearable systems (n = 47), absence of quantitative validation (n = 36), non-construction context (n = 29), conceptual or design-only studies (n = 18), and medical-only applications without construction transferability (n = 8). The final corpus included 76 records. Of these, 63 empirically validated records were used for performance benchmarking, quality scoring, and TRL analysis; 13 contextual or broader wearable records were retained only for background framing and transferability interpretation. The full selection process is documented in the PRISMA flow diagram in Figure 2.

3.4. Eligibility Criteria (PICOS Operationalization)

Eligibility criteria were operationalized using the PICOS framework with measurable thresholds. The population included construction workers or participants performing validated construction-simulated tasks such as repetitive lifting (>10 kg loads), scaffold climbing, overhead drilling, or sustained bending. Studies involving general industrial workers were included only if construction transferability was explicitly demonstrated.

The intervention required textile-integrated sensing systems in which sensors were embedded within or permanently affixed to garment structures. Removable or externally clipped devices were excluded. Eligible outcomes included at least one quantitative performance metric, such as classification accuracy, sensitivity, specificity, F1-score, balanced accuracy, detection latency, or error rate. Studies reporting only descriptive or qualitative findings without statistical validation were excluded.

Eligible study designs included laboratory experiments, controlled pilot deployments, and field-based validation under real or simulated construction conditions involving physical task execution. Purely conceptual frameworks, simulation-only computational models, and studies without empirical validation were excluded. The detailed operationalization of the eligibility criteria used during screening and full-text assessment is summarized in Table 2 to ensure transparency, reproducibility, and reusability in future construction informatics and smart PPE benchmarking studies. The PICOS eligibility criteria in Table 2 apply to the 63 empirically validated records used for benchmarking. Contextual review/source records and broader wearable/context records were retained only for background framing and transferability interpretation; they were excluded from performance benchmarking, quality scoring, and TRL analysis.

Table 2. Operationalized eligibility criteria based on the PICOS framework.

PICOS Component	Operational Definition	Inclusion Threshold	Exclusion Rule	Rationale
Population	Human participants performing construction work or validated construction-simulated physical tasks (e.g., lifting $\geq$ 10 kg, scaffold climbing, overhead drilling, sustained bending)	Study sample explicitly includes construction workers or participants performing construction-equivalent tasks with physical workload characteristics comparable to site operations	General industrial, laboratory-only physiological studies, or clinical populations without demonstrated construction transferability	Ensures contextual relevance and ecological validity for construction safety applications
Intervention	Garment-integrated sensing systems in which sensors are embedded within, woven into, printed on, or permanently affixed to textile-based apparel	Textile-integrated smart garments (e.g., vests, shirts, harnesses) with embedded sensing hardware forming part of garment structure	Standalone wearable devices (e.g., wristbands, smartwatches, helmet-only systems), externally clipped sensors, removable modules not structurally integrated into textiles	Maintains architectural homogeneity and avoids methodological heterogeneity across fundamentally different wearable categories
Comparator	Not required for eligibility	Comparative validation against baseline measures, ground truth systems, or gold-standard instruments when available	Absence of comparator does not exclude study, provided quantitative validation metrics are reported	Reflects exploratory and prototype nature of smart garment research while encouraging benchmarking where available
Outcomes	Quantitative performance metrics evaluating detection, classification, or monitoring capability	At least one measurable metric (e.g., accuracy, sensitivity, specificity, F1-score, balanced accuracy, detection latency, error rate) derived from empirical validation	Studies reporting only conceptual frameworks, qualitative descriptions, or narrative feasibility without statistical validation	Ensures empirical rigor and enables cross-study performance synthesis
Study Design	Empirical validation involving physical testing of smart garment systems	Laboratory experiments, controlled pilot deployments, or field validation under real or simulated construction conditions involving physical task execution	Purely conceptual studies, simulation-only computational models without physical testing, reviews, editorials, and commentary articles	Restricts corpus to experimentally validated systems to support defensible performance benchmarking

3.5. Data Extraction and Validation Framework

A standardized extraction template was developed and pilot-tested on 15 randomly selected studies to ensure clarity and consistency. Data extraction was conducted independently by two reviewers. Extracted variables included bibliometric metadata; garment configuration; sensor types and specifications; sampling frequency; signal preprocessing techniques; feature extraction methods; machine learning architecture; cross-validation strategy; sample size; validation duration; validation environment; environmental realism classification; performance metrics; power management strategy; interoperability description; reported limitations; and estimated TRL. After independent extraction, datasets were cross-compared using automated spreadsheet reconciliation. Numerical discrepancies exceeding 5% triggered re-examination of source manuscripts. Final harmonized datasets were archived for reproducibility. The full extraction codebook (variable definitions, permitted values, and decision rules for ambiguous reporting) is provided in Supplementary File S1, Sheet S2. The harmonized extraction dataset, also in Supplementary File S1, Sheet S2 classifies all 76 records by corpus role, garment type, sensing modality, hazard domain, validation context, reported performance, quality score, and TRL. This machine-readable schema is designed for reuse in future construction informatics benchmarking of smart PPE systems.

3.6. Quality Assessment and Risk of Bias

Methodological quality was evaluated across six domains: sample representativeness, validation rigor, performance transparency, statistical robustness, environmental realism, and reproducibility disclosure. Each domain was scored on a 0–2 scale (0 = insufficient; 1 = partial; 2 = robust), yielding a total possible score of 0–12; studies scoring ≥9 were classified as high quality, 6–8 as moderate, and ≤5 as low quality. Domain definitions and scoring thresholds are provided in Table 3. A score of 0 was assigned when the required information for that domain was not reported or was not verifiable from the manuscript; missing reporting was not imputed. When a study could plausibly meet two adjacent scores, reviewers applied a conservative rule (selecting the lower score unless explicit evidence supported the higher score).

Table 3. Methodological quality assessment rubric (0–12 scoring framework).

Domain	Score 0 Definition	Score 1 Definition	Score 2 Definition	Maximum Score
Sample Representativeness	Sample size <10 or convenience sample with no demographic/ context description	Sample size 10–29 with partial description of participant characteristics	Sample size ≥30 or field-based sample with clear demographic and occupational description	2
Validation Rigor	No external validation; single uncontrolled experiment	Controlled laboratory validation or limited pilot test (<1 work shift equivalent)	Field validation under realistic construction conditions or multi-session controlled validation	2
Performance Transparency	Performance metric vaguely described; no clear calculation method	Basic metrics reported (e.g., accuracy only) without confusion matrix or class balance clarification	Comprehensive metrics reported (e.g., accuracy, sensitivity, specificity, F1-score) with clear computational basis	2
Statistical Robustness	No statistical testing or validation split described	Basic train/test split or limited validation without cross-validation	Cross-validation, independent test set, or statistically justified validation procedure clearly described	2
Environmental Realism	Fully simulated environment without physical task replication	Laboratory experiment involving physical task replication but controlled environment	Real or semi-operational construction site testing involving authentic task conditions	2
Reproducibility Disclosure	Insufficient methodological detail to replicate system configuration or evaluation	Partial system description without complete parameters or preprocessing details	Detailed sensor specifications, preprocessing steps, ML architecture, and validation protocol clearly documented	2

Prior to full scoring, two reviewers calibrated the scoring interpretation on 10 pilot studies. Disagreements were recorded per domain and resolved by consensus after re-checking the source text; if consensus was not reached, the lower (more conservative) score was assigned and documented. Inter-rater reliability for total quality scores was assessed using a two-way random-effects ICC (ICC = 0.89). For example, for "performance transparency," studies reporting accuracy without class balance or confusion-matrix detail were scored 1, while studies reporting multiple metrics with explicit calculation basis were scored 2.

A limitation of the rubric is that all six domains are weighted equally. Although environmental realism and validation rigor are arguably more consequential for construction deployment, equal weighting was retained to avoid arbitrary weight assignment in the absence of an empirically derived weighting scheme. A formal differential-weighting approach would require prospective validation against deployment outcomes not available in the current corpus. Domain-level scores for the six quality domains are provided in Supplementary File S1, Sheet S2 for the 63 empirical benchmark records. Contextual and broader records were not quality scored. A sensitivity analysis was conducted by

double-weighting validation rigor and environmental realism, the two quality domains most directly related to construction deployment readiness. Under this weighting, no empirical record changed quality class, because the overall score range remained narrow and no low-quality records were present. The overall interpretation of quality distribution was therefore unchanged.

3.7. Quantitative Synthesis and Statistical Analysis

Meta-analysis was not appropriate because included studies differed substantially in outcome definitions, task protocols, and validation designs (laboratory, pilot, and field), making pooled estimates potentially misleading. Instead, a structured descriptive synthesis was conducted using median and IQR summaries stratified by validation context and sensing modality. For each unique task per study, one primary performance metric was extracted; when multiple metrics were equally emphasized, F1 or balanced accuracy was prioritized for class-imbalanced outcomes and accuracy otherwise, reducing double-counting and improving interpretability. Quantitative outcomes such as accuracy, F1-score, RMSE, AUC, and detection latency were summarized numerically only within comparable hazard-domain and validation-context strata. Qualitative outcomes, including feasibility demonstrations, worker-use descriptions, and pilot reports without formal metrics, were synthesized narratively and were not pooled with quantitative performance results.

A pre-specified comparability framework standardized only commensurate elements: (i) validation context, (ii) metric type (classification, detection/localization, or physiological regression), and (iii) reported time/latency units when explicitly stated. Cross-domain standardization (e.g., posture vs. heat stress) and comparisons across non-equivalent metrics (e.g., accuracy vs. F1 vs. AUC) were intentionally avoided. Quantitative summaries are therefore reported within comparable strata only, while cross-strata differences are interpreted qualitatively. Given incompatible outcome definitions and inconsistent validation designs, pooled effect estimation was not performed.

Subgroup analyses compared laboratory versus field validation, physiological versus kinematic sensing systems, and classical machine learning versus deep learning models. Sensitivity analysis excluded low-quality studies to test robustness; because S2 contains zero low-quality records among the 63 empirical records, this analysis was not applicable. Spearman's rank correlation evaluated associations between methodological quality and reported performance. Publication growth across the review window was assessed descriptively: Wave 1 ($\leq$2012) contained 7 records, Wave 2 (2013–2022) contained 47 records, and Wave 3 (2023–2026) contained 22 records, with an average of approximately 7 records per year in Wave 3 compared with fewer than 5 per year during 2013–2022. Analyses were conducted in R (Version 4.3.1), with statistical significance set at $p < 0.05$.

3.8. Technological Readiness Level (TRL) Operationalization

TRLs were assigned using an adapted framework: TRL 3 indicated laboratory feasibility; TRL 4, controlled prototype validation; and TRL 5, pilot or field validation under realistic construction-equivalent conditions. No empirical record in the corpus was assigned TRL 6 or higher, reflecting the absence of studies demonstrating sustained operational deployment beyond a single field trial. Two independent reviewers assigned TRLs, achieving substantial agreement (weighted Cohen's $\kappa = 0.83$). The concentration of systems at TRL 4 ($n = 43$, 68%) indicates a field dominated by controlled prototype validation that has not yet transitioned to operational deployment.

3.9. Bias Mitigation

Bias was reduced through multi-database searching and inclusion of indexed conference proceedings to limit journal-only selection effects. Selective reporting was evaluated

through the performance-transparency domain, and potential laboratory-related performance inflation was examined using lab-versus-field subgroup comparisons. Language restrictions were acknowledged as a limitation.

4. Results

All quantitative summaries reported below are stratified by hazard domain and validation context; performance across strata is not interpreted as directly comparable because datasets, labeling rules, and task protocols differ substantially.

4.1. Corpus Characteristics and Bibliometric Structure

The systematic screening process yielded 76 records satisfying all predefined eligibility criteria. Consistent with the tiered scope described in Section 3.1, Supplementary File S1, Sheet S2 classifies these records as: 18 core/adjacent construction smart-garment studies (23.7%), 45 transferable smart-garment studies from healthcare, occupational safety, sports, and rehabilitation assessed for construction relevance (59.2%), 2 broader wearable/context records (2.6%), and 11 contextual review and synthesis sources (14.5%). All quantitative benchmarking uses the 63 empirically validated records (core + transferable). The 13 contextual and broader wearable records are cited in the Background and Discussion sections for framing only and are excluded from all performance statistics, quality scoring, and TRL analysis. A representative profile of included studies is in Table 4; the complete classified dataset is in Supplementary File S1, Sheet S2. As documented in the PRISMA flow diagram (Figure 2), 742 records were initially retrieved, 601 unique records remained after deduplication, and 76 records were included following dual screening and full-text eligibility assessment.

Validation context analysis of the 63 empirical records reveals a strong predominance of laboratory-based testing. Each record was assigned to its primary validation context: 53 records (84%) were validated under laboratory, prototype, or controlled conditions; 3 records (5%) in pilot or semi-controlled settings; and 7 records (11%) under field or field-simulated conditions [18,27–32]. All seven field or field-simulated empirical records were classified as core/adjacent construction evidence in Supplementary File S1, Sheet S2, although their level of site realism varied from field-simulated validation to construction-site deployment. This suggests that the field-validation gap is not caused only by the inclusion of transferable non-construction records, but also reflects the limited number of operationally validated smart-garment systems overall. Seven empirical records were counted as field or field-simulated for validation-context stratification purposes. However, only six of these seven were assigned TRL 5, because TRL 5 required both realistic environmental exposure and sufficient validation maturity (quantitative performance reported under site-realistic conditions). The exception is Akhavian and Behzadan [28], which was retained in the broader field/field-simulated category on the basis of its field-simulated outdoor task design but classified at TRL 4 because its validation was simulation-oriented rather than sustained operational deployment on a live construction site.

Note that the seven-record field-validation count uses a broader operational definition that includes records labeled field, field/applied, field-simulated, and field/construction site in Supplementary File S1, Sheet S2. All performance summaries in Section 4.3 are stratified by validation context; laboratory and field results are not pooled or directly compared. Validation context labels used in S2 are defined as follows for interpretation purposes: Laboratory = controlled indoor or bench setting; physical task may be simulated; no realistic site exposure. Pilot/semi-controlled = prototype tested with limited realism, controlled participants, or short-duration trial outside a purely laboratory environment. Field-simulated = construction-equivalent task or outdoor/semi-realistic environment, but

not a live construction site. Field-applied = application-oriented validation in a practical work setting with limited duration, incomplete task realism, or incomplete operational integration. Field/construction site = validation conducted on an active or realistic construction site with construction tasks and site exposure.

Primary hazard-domain classification of the 63 empirical benchmark records shows that fatigue and physiological monitoring is the largest category (n = 39, 62%), followed by ergonomic posture/postural risk (n = 11, 17%), heat-stress monitoring (n = 6, 10%), multi-hazard/safety management (n = 4, 6%), durability/washability (n = 2, 3%), and worker localization/proximity (n = 1, 2%). No record was classified as fall detection as its primary hazard domain. These counts are mutually exclusive and are based on the Primary Hazard Domain column in Supplementary File S1, Sheet S2. Some records address secondary hazards, but those secondary mentions are not double-counted in the primary-domain totals.

Methodological quality assessment of the 63 empirical records (0–12 scale) yielded a median overall score of 8 (IQR: 7–9). Based on predefined thresholds, 8 records (13%) were classified as high quality ($\geq$9), 55 records (87%) as moderate quality (6–8), and 0 records as low quality ($\leq$5). Score distribution was: 6 (n = 1), 7 (n = 17), 8 (n = 37), and 9 (n = 8). Inter-rater reliability for quality scoring was ICC = 0.89 (two-way random-effects model), indicating strong agreement between reviewers. For title and abstract screening, Cohen's κ = 0.86 (calculated on a 25% random subsample, $n \approx 150$), indicating substantial agreement. Both statistics exceed accepted thresholds (ICC > 0.75; κ > 0.61). Quality scoring in Supplementary File S1, Sheet S2 is applied only to the 63 empirically validated records; contextual and broader wearable records are excluded from quality scoring and TRL analysis.

Publication-year distribution across the three developmental waves was: Wave 1 (2000–2012, n = 7), reflecting early-phase textile-sensing feasibility work; Wave 2 (2013–2022, n = 47), a period of accelerated IoT-enabled prototyping and supervised machine learning integration; and Wave 3 (2023–2026, n = 22), showing growing multimodal and edge-AI architectures with increasing field validation. Wave counts sum to 76. Annual record counts by year were: 2007 = 1, 2008 = 1, 2011 = 2, 2012 = 3, 2015 = 1, 2016 = 3, 2017 = 3, 2018 = 11, 2019 = 4, 2020 = 11, 2021 = 8, 2022 = 6, 2023 = 4, 2024 = 9, and 2025 = 8, 2026 = 1. The acceleration from Wave 1 to Wave 2 is substantial; Wave 3 shows approximately seven records per year across 2023–2026, compared with fewer than five per year during 2013–2022.

A temporary reduction in records dated 2020 is visible in the dataset. While this coincides with global research disruption from the COVID-19 pandemic, the record count alone does not support a causal claim, and no causal attribution is made. TRL distribution across the 63 empirical records was: TRL 3 (n = 14, 22%), TRL 4 (n = 43, 68%), and TRL 5 (n = 6, 10%). No empirical record in Supplementary File S1, Sheet S2 was assigned TRL 6 or higher. The concentration at TRL 4 indicates a field characterized by controlled prototype validation that has not yet transitioned to sustained operational deployment (Figure 3).

Keyword co-occurrence analysis (Figure 4) was conducted using VOSviewer, version 1.6.21, (minimum occurrence threshold = 5; full counting method; total included keywords = 112). Three dominant clusters emerged. The first cluster centers on computational constructs ("classification," "deep learning," "feature extraction"), the second on physiological and thermal monitoring ("heart rate," "heat stress," "fatigue"), and the third on kinematic and biomechanical sensing ("IMU," "posture," "acceleration"). The temporal overlay suggests that computational keywords increase in density in later years, consistent with the transition from rule-based detection to data-driven inference architectures. This bibliometric structure aligns with the technological synthesis presented below.

This distribution suggests that the current evidence base is weighted toward controlled experimentation rather than operational deployment.

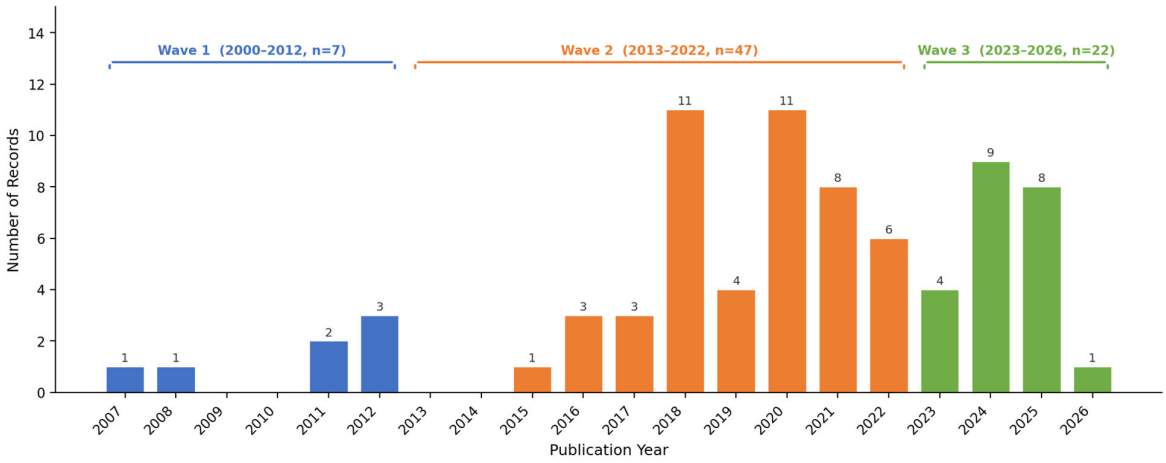


Figure 3. Annual record counts for the 76-record corpus by publication year, grouped into three developmental waves. Wave 1 (2000–2012, n = 7) represents early-phase textile-sensing feasibility. Wave 2 (2013–2022, n = 47) represents IoT-enabled prototyping and supervised machine learning integration. Wave 3 (2023–2026, n = 22) represents multimodal sensing, edge-AI architectures, and increasing field validation. Counts are based on the Year column in Supplementary File S1, Sheet S2.

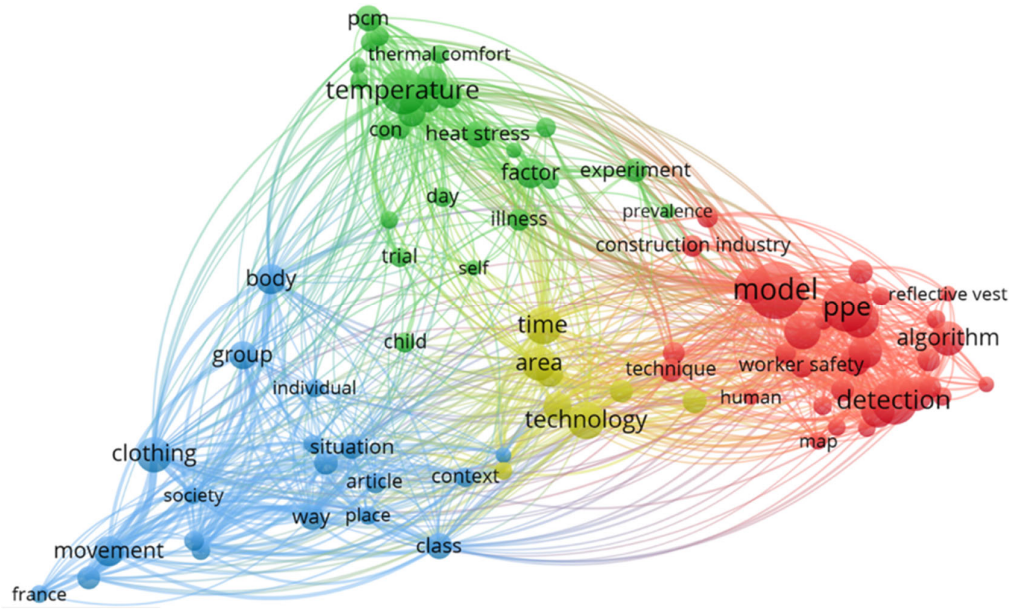


Figure 4. Term co-occurrence network showing thematic structure and research clusters in smart garment studies (2000–2026).

4.2. Technological Architecture: Sensing, Textile Integration, and Computation

The following architecture statistics are drawn from the 63 empirically validated records and include both core/adjacent and transferable studies. Because the S2 sensor modality field uses free-text entry with varying granularity, exact per-modality counts are approximate; they are reported here as recorded in S2 without normalization. Textile ECG electrodes were the most frequently reported primary sensing modality (eight records explicitly coded), alongside IMU or accelerometer-based sensing. Multimodal sensing configurations, combining physiological and kinematic sensing, appeared across both construction-direct and transferable records. The following paragraph-level architecture

summary draws from S2 extraction data; where specific counts differ from the original manuscript, S2 values take precedence.

Table 4. Study characteristics of representative empirically validated garment-integrated sensing systems included in the review. Field-oriented and construction-adjacent examples include Rashidi et al. [18], Edirisinghe and Gunathilake [27,29], Ray and Teizer [31], and Keränen et al. [30]. All entries are classified as core/adjacent or transferable smart-garment evidence in Supplementary File S1, Sheet S2 and satisfy the garment-integration criterion (sensors embedded in or permanently integrated into textile apparel). The two localization-module entries (Ray and Teizer [31]: UWB positioning module sewn into a safety vest; Rashidi et al. [18]: GPS module integrated within a multi-sensor safety vest alongside IMU and ECG) were retained because the positioning hardware is structurally built into the vest rather than clipped on or carried separately, consistent with the garment-integration criterion in Table 2; they are distinct from excluded standalone trackers, wristbands, or externally clipped tags that are not affixed to the garment structure. No review papers, conceptual papers, or unverified studies appear in this table. The maximum TRL assigned is TRL 5; no empirical record in S2 reached TRL 6. The complete 76-record classified dataset, including corpus-role designations, verification status, and DOIs, is provided in Supplementary File S1, Sheet S2.

Study (S2 Row)	Garment Type	Primary Sensing	Hazard Domain	Corpus Role	Validation Context	Reported Performance
Rashidi et al., 2025, [18] (S2 row 33)	Multi-sensor safety vest	IMU, ECG, GPS	Multi-hazard	Core/adjacent	Field (construction)	F1 = 0.88
Edirisinghe & Gunathilake, 2025 [29] (S2 row 4)	Smart vest (IoT)	Temp, HR, IoT sensors	Heat stress	Core/adjacent	Field/applied	System validated in field
Ray & Teizer, 2012 [31] (S2 row 15)	Safety vest (UWB)	UWB positioning module	Localization	Core/adjacent	Field (construction site)	Position error ~20 cm
Keränen et al., 2025 [30] (S2 row 17)	Wearable smart suit	IMU wearable sensors	Fatigue (ML)	Core/adjacent	Field (construction site)	ML fatigue trend
Jebelli et al., 2018 [32] empirical field study (S2 row 7)	Vest IMU harness	EEG, GSR, HRV	Worker stress	Core/adjacent	Field (construction site)	AUC = 0.87
Jebelli et al., 2019 [33] (S2 row 24)	Smart shirt (ECG)	Textile ECG electrodes	Cardiovascular/ fatigue	Core/adjacent	Laboratory	RMSE = 3.2 bpm
Zhang Z. et al., 2021 [23] (S2 row 20)	Smart shirt (e-textile)	Conductive yarn pathways	Durability/ washability	Core/adjacent	Laboratory (wash cycling)	Signal loss <30% @ 25 cycles
Schall et al., 2018 [34] (S2 row 16)	Vest/harness (IMU)	IMU, accelerometer	Ergonomic risk	Core/adjacent	Laboratory	Accuracy = 87%
Akhavian & Behzadan, 2018 [28] (S2 row 1)	Vest-mounted IMU	IMU, accelerometer	Activity recognition	Core/adjacent	Field-simulated	Accuracy = 89%
Edirisinghe & Gunathilake, 2026 [27] (S2 row 6)	IoT smart vest	Temp/physiol. IoT sensing	Heat stress	Core/adjacent	Field/applied	IoT smart-vest system
Martins et al., 2024 [17] (S2 row 18)	E-textile smart vest	sEMG and IMU	Posture/ ergonomic risk	Transferable (occupational)	Laboratory	Posture monitoring system
Hossain et al., 2024 [35] (S2 row 9)	Smart cooling vest	Cooling vest/thermal sensors	Heat stress	Core/adjacent	Prototype/ laboratory	Prototype cooling vest

IMU-based systems primarily targeted ergonomic risk classification and fall detection. Sampling frequencies ranged from 20 to 200 Hz, enabling posture segmentation and impact detection. Physiological systems relied on conductive textile electrodes for ECG acquisition and heart rate variability derivation. Motion artifact interference during high-mobility tasks was a recurring limitation noted across records.

Architecture extraction in S2 used free-text fields for garment type, sensing modality, and computational approach; therefore, exact normalized modality counts were not treated as inferential statistics. Across the 63 empirical records, the dominant design pattern was textile-based worker-worn sensing, most often implemented through safety vests, smart shirts, harness-integrated systems, or modular garment platforms. IMU and accelerometer

systems were primarily used for posture classification, activity recognition, fall detection, and ergonomic risk assessment. Textile ECG electrodes, heart rate, heart rate variability, and temperature sensors were used for fatigue, cardiovascular load, and heat-stress applications. Multimodal systems combining physiological, kinematic, and environmental signals were increasingly common in later corpus records. However, durability, washability, full-shift battery endurance, and system integration were inconsistently reported across records, limiting quantitative comparison of architectures. Computational frameworks transitioned across publication waves, from rule-based threshold detection in earlier records toward supervised machine learning and, in more recent records, deep learning architectures including CNN, LSTM, and hybrid configurations. Table 5 summarizes the S2-verified corpus structure for the 63 empirically validated records.

Table 5. S2-verified corpus structure for the 63 empirically validated records.

Dimension	Category	*n*	%
Validation context	Laboratory/prototype/controlled	53	84%
	Pilot/semi-controlled	3	5%
	Field/field-simulated	7	11%
Quality classification	High (≥9/12)	8	13%
	Moderate (6–8/12)	55	87%
	Low (≤5/12)	0	0%
TRL	TRL 3	14	22%
	TRL 4	43	68%
	TRL 5	6	10%
	TRL 6+	0	0%

Durability and washability testing were explicitly reported in a minority of records, and long-duration (more than 8 h) validation was similarly rare, indicating limited evaluation of lifecycle performance under real-world construction constraints.

Technological evolution in smart garments is driven more by system-level integration strategies than isolated sensor improvements, emphasizing robustness under construction variability as the dominant design driver.

Sustainability and Lifecycle Reporting in the Corpus

A keyword audit of the 63 empirical benchmark records was conducted to assess sustainability-relevant reporting using terms including battery, energy, power, charging, washability, durability, laundering, lifecycle, material, textile waste, e-waste, and disposal. The audit revealed that only 11 of 63 empirical records (17%) explicitly reported at least one lifecycle-relevant sustainability variable. The most commonly reported variables were battery autonomy or power consumption (n = 7), laundering durability or signal degradation after repeated use (n = 5), and system lifetime or sensor wear (n = 3). No record in the corpus provided a full lifecycle assessment, end-of-life disposal analysis, or material sustainability evaluation. This low reporting rate supports the *Sustainability* journal framing of this review: sustainability claims for smart garments remain substantially underreported in the empirical literature, and lifecycle impacts of garment-integrated electronics, including battery waste, conductive textile disposal, and electronic component degradation, are not yet systematically addressed. Future research should treat sustainability reporting as a required component of smart-garment validation, not an optional addition.

4.3. Performance Benchmarking and Quantitative Synthesis

Figure 5 presents the evidence maturity matrix, cross-tabulating all 63 empirically validated records by hazard domain and validation context. The matrix directly visualizes

the laboratory-dominance pattern and supports the deployment-maturity framework in Section 5.6. Figure 5 uses the primary hazard domain recorded in Supplementary File S1, Sheet S2 to maintain mutually exclusive counts; non-mutually exclusive hazard-domain mentions are discussed separately and are not used for the matrix totals. Fatigue and physiological monitoring is the most represented primary hazard domain among the 63 empirical records (n = 39, 62%), reflecting the corpus's substantial reliance on transferable healthcare, sports, and occupational-health literature; ergonomic posture/postural risk is the largest construction-oriented category (n = 11, 17%). Fall detection has no dedicated primary-domain record in the verified corpus (n = 0), and worker localization/proximity is represented by a single field-validated record (n = 1), indicating that these frequently cited construction hazards remain substantially underrepresented in garment-integrated empirical evidence. Because each record is assigned to a single primary hazard domain, secondary hazard associations are not reflected in the matrix; four records classified under multi-hazard/safety management inherently combine two or more hazard types (e.g., Rashidi et al., S2 row 33, integrates ergonomic, cardiovascular, and localization sensing via IMU, ECG, and GPS). These non-mutually exclusive hazard-domain mentions are noted here narratively and are not double-counted in the matrix. The darker cells show higher number of records.

Hazard Domain	Laboratory/Prototype	Pilot/Semi-Controlled	Field/Field-Simulated	Total (n)
Ergonomic Posture/Postural Risk	9	1	1	11
Fatigue & Physiological Monitoring	35	2	2	39
Heat-Stress Monitoring	4	0	2	6
Fall Detection	0	0	0	0
Worker Localization/Proximity	0	0	1	1
Multi-Hazard/Safety Management	3	0	1	4
Durability/Washability	2	0	0	2
Total	**53**	**3**	**7**	**63**

Figure 5. Evidence maturity matrix for the 63 empirical benchmark records, cross-tabulated by primary hazard domain and validation context. Validation-context column totals match Table 5: laboratory/prototype/controlled (n = 53), pilot/semi-controlled (n = 3), and field/field-simulated (n = 7). Contextual and broader records (n = 13) are excluded from this matrix.

To avoid invalid comparisons across studies, quantitative summaries were restricted to studies sharing comparable hazard domains, validation contexts (laboratory, pilot/simulated, or field), and metric definitions. Standardization was not applied across different task types or non-equivalent metrics (e.g., accuracy versus F1-score). For each study, one primary metric per unique task was extracted to prevent double-counting, following the metric emphasized by the original authors. Supplementary File S1, Sheet S7, reports the median, interquartile range, and range of the primary performance metric for every primary hazard domain–validation context combination; only one cell (ergonomic posture, laboratory, accuracy) contains enough same-metric records for a genuine median/IQR summary, while most cells contain a single comparable value or no directly comparable numeric value at all, reflecting the corpus-wide absence of standardized benchmarking discussed in Section 5.6.

Within the S2-coded ergonomic posture domain (n = 11 under the primary hazard-domain classification used in Figure 5), five of nine laboratory records reported a directly comparable accuracy metric (median 92%, IQR 87–95%, range 87–97%; Supplementary

File S1, Sheet S7); the single field record reported 89% accuracy and the single pilot record reported 88% accuracy. Because only one record each is available in the field and pilot strata, these single values cannot support a generalizable laboratory-to-field gap claim for this domain; they are reported here for transparency rather than as evidence of a systematic difference. Because no empirical records were rated low quality, low-quality exclusion sensitivity analysis was not applicable.

No record in the verified 63-record corpus was classified under fall detection as its primary hazard domain (n = 0; see Figure 5); fall-related sensing in this corpus occurs only as a secondary capability within broader IMU-based ergonomic or multi-hazard systems, not as a dedicated, independently benchmarked fall-detection function. High sensitivity figures for fall detection reported in prior wearable-sensing literature should therefore not be assumed to transfer to garment-integrated construction systems without dedicated validation.

Heat-stress monitoring records (n = 6 under the primary hazard-domain classification used in Figure 5) [27,29,36] report thermal-comfort or system-validation outcomes; none of the six records report a directly comparable numeric error metric (e.g., RMSE) in either laboratory or field/field-simulated conditions (Supplementary File S1, Sheet S7), so a quantitative field-versus-laboratory error comparison cannot be supported for this domain from the current corpus.

A subset of fatigue-estimation systems integrating physiological and kinematic data [32–34] (n = 17 of the 39 records classified under Fatigue & Physiological Monitoring in Figure 5) reported stronger classification performance than single-modality systems, consistent with sensor-fusion benefits seen in ergonomic and cardiovascular domains. The corpus-level association between methodological quality and reported performance is reported in Section 4.4.

Only one record in the verified 63-record corpus was classified under worker localization/proximity as its primary hazard domain: Ray and Teizer [31], which reported sub-meter positional error under field conditions using UWB integration (position error $\approx$ 20 cm). No GNSS-based positioning comparator is present among the 63 empirical records; claims about the relative limitations of satellite-dependent indoor positioning made in prior wearable literature cannot be evaluated from this corpus and should not be inferred from it.

Benchmarking variability appears consistent with validation context and sensing configuration as major sources of performance variation, though this pattern should not be interpreted causally, the same systems were not tested in both laboratory and field settings, and other differences between study samples may contribute to the observed gap.

4.4. Analytical Interpretation of Performance Variation

Beyond descriptive summaries, an exploratory analytical assessment was conducted to identify potential drivers of performance variation across studies. Because outcome definitions and experimental protocols remained heterogeneous, formal meta-analysis was not appropriate; however, the harmonized extraction dataset enabled structured pattern interpretation.

Validation context emerged as a consistent explanatory factor. Systems evaluated in laboratory settings reported higher performance than those validated under operational field conditions, suggesting that environmental variability, task complexity, and uncontrolled worker behavior reduce classification stability outside controlled experiments. Thus, performance differences likely reflect contextual realism rather than purely technological capability.

Sensing configuration also influenced outcomes. Multimodal systems integrating physiological and kinematic sensing often reported stronger performance within comparable controlled studies, although the evidence remains heterogeneous and predominantly laboratory-based.

Computational architecture showed an association with performance dispersion. Deep learning approaches often reported higher peak performance but also greater variability compared with classical machine learning models, suggesting increased sensitivity to dataset composition and sample size when training data are limited or context-specific.

An exploratory Spearman rank correlation was computed between total methodological quality score (0–12) and the primary reported performance metric extracted from S2 for each empirical benchmark record (n = 63). Quality scores ranged only from 6 to 9, with no low-quality records, producing restricted variance. The association was weak and non-significant ($\rho = 0.28$, $p = 0.27$). This result should be interpreted as inconclusive rather than evidence that quality has no relationship with performance; the narrow score range limits statistical power and precludes meaningful regression modeling. Structured pattern synthesis was used instead to identify recurring associations among validation context, sensing configuration, and reported performance.

5. Discussion

Smart garments for construction safety show clear technical advancement across the reviewed evidence, but adoption remains limited by practical and organizational constraints. Multimodal sensing often reported stronger performance than single-sensor systems in controlled evaluations, although this pattern should be interpreted cautiously because the evidence is heterogeneous and predominantly laboratory-based. Edge processing supports real-time alerts, and garment-integrated sensing is architecturally more stable than externally attached devices. Most systems, however, remain laboratory-validated. Only 7 of 63 empirical records were field or field-simulated, and reported performance values should be interpreted as controlled-experiment results rather than field benchmarks.

5.1. Engineering, Governance, and Implementation Barriers

Across the reviewed studies, privacy and surveillance concerns were consistently reported as adoption barriers. Although smart garments are intended for protection, biometric monitoring may be interpreted as productivity or disciplinary tracking, which can undermine trust and voluntary use [34,37,38]. Adoption depends on more than sensing accuracy; it also depends on credible governance, including who controls the data, who can access it, how long it is retained, and whether it can be repurposed beyond safety [39,40]. Without clear boundaries aligned with labor and privacy expectations, governance risk can delay implementation even when technical performance is strong.

To reduce workforce-surveillance risk, the literature implies that implementation should adopt a safety-first governance baseline: (i) data minimization (collect only what is needed for safety decisions), (ii) purpose limitation (explicitly prohibit disciplinary or productivity uses of biometric signals), (iii) access control and transparency (define who can view identifiable data and provide workers clear notice), and (iv) retention limits (prefer short retention or aggregation where feasible). Framing these safeguards as part of the deployment plan helps position smart garments as protective PPE extensions rather than general monitoring infrastructure.

The corpus shows that some studies reported privacy-by-design approaches, including federated learning and localized processing, as strategies to reduce transmission of raw biometric data [41]. Available evidence indicates that successful implementation requires aligning smart garments with existing safety culture and clearly communicating their

purpose as safety tools rather than monitoring systems. Adoption outcomes are shaped as much by governance credibility and worker trust as by technological capability, positioning smart garments as sociotechnical systems rather than purely engineering solutions.

5.2. Operational Constraints

Durability and power management remain primary deployment barriers with direct sustainability implications. Short garment lifespans resulting from laundering degradation, mechanical stress, and environmental exposure contribute to increased electronic and textile waste, an underreported sustainability cost of wearable sensing adoption at construction scale. Long-term performance under these conditions is rarely validated, limiting scalability [21–23]. Across studies, energy autonomy is a stronger bottleneck than sensing precision, constraining full-shift usability despite high detection performance. Battery replacement cycles and disposal also represent material sustainability concerns not addressed in the current corpus. Although energy-efficient strategies and energy harvesting concepts have been explored [26], these remain experimental and have not been evaluated against lifecycle sustainability metrics.

5.3. Economic Feasibility and Adoption

Economic feasibility is acknowledged but insufficiently evaluated. Existing cost–benefit estimates are largely model-based and therefore indicative rather than definitive [25]. From a sustainability standpoint, the economic case for smart garments must extend beyond unit cost to encompass avoided injury costs, reduced workers' compensation claims, long-term productivity retention, and the social cost of preventable fatalities, costs that are currently externalized rather than captured in procurement decisions. Adoption appears influenced by firm size and digital maturity, suggesting that scalable designs and incremental PPE integration may improve practical feasibility, particularly for small and medium-sized construction enterprises that bear disproportionate injury burdens. A lifecycle cost framework that integrates safety, durability, and maintenance costs would provide a more complete basis for evaluating the economic sustainability of smart garment adoption (Table 6).

Table 6. Synthesized implementation barriers and evidence-supported mitigation approaches.

Barrier Category	Primary Challenge	Reported Approaches in the Literature
Privacy and trust	Perceived biometric surveillance and data governance uncertainty	Privacy-by-design architectures, federated learning, localized processing [41]
Durability	Signal degradation under repeated use and laundering	Textile-integrated pathways, encapsulated electronics, flexible PCB strategies [21,23]
Power management	Limited battery life during extended shifts	Energy-efficient processing and exploratory harvesting approaches [26]
Economic adoption	High upfront investment and uncertain return	Pilot-based implementation and staged adoption models reported in industry studies [25]

Deployment barriers across the corpus are largely systemic rather than purely technical, highlighting that adoption readiness depends on durability, governance, and integration constraints as much as sensing performance. In practice, the cost of smart garments would likely be borne by contractors, employers, or project owners rather than individual workers. This creates an equity concern because large general contractors may be able to pilot and maintain smart-garment systems, while smaller subcontractors, whose workers may face higher risk exposure, may lack the capital and digital infrastructure required for adoption. Within the SDG 8 framing, equitable deployment therefore requires attention to who pays, who benefits, and whether high-risk worker groups are excluded from safety technologies because of firm-level resource constraints.

5.4. Smart Garments Relative to Alternative Monitoring Technologies

Compared with smart helmets or wrist wearables, garments offer improved signal stability and multimodal integration, although external devices often face lower adoption barriers. Vision-based systems enable non-contact monitoring but suffer from occlusion and surveillance concerns, while exoskeletons prioritize ergonomic support rather than sensing. Smart garments, therefore, occupy an intermediate position between passive wearables and infrastructure-based monitoring, offering deeper worker-level sensing but facing cost, durability, and maintenance constraints. Rather than replacing other technologies, they should be viewed as complementary elements within a layered safety ecosystem.

5.5. Deployment-Maturity Framework

The deployment-maturity framework proposed in this review organizes readiness across five dimensions: (i) technical performance: sensing accuracy, detection latency, and model robustness; (ii) validation maturity: the extent of testing under realistic construction conditions rather than controlled laboratory settings; (iii) operational durability: washability, mechanical resilience, and full-shift power autonomy; (iv) human and organizational acceptance: worker comfort, trust, and data governance transparency; and (v) systems integration: interoperability with construction safety platforms, BIM models, or digital twins. Several multidimensional readiness frameworks exist in adjacent fields, including the Capability Maturity Model (CMM) in software engineering and ISO 16290 [42] in space systems, yet none addresses the governance, durability, and information-system integration dimensions relevant to construction safety informatics. This framework differs from NASA TRL in two important ways, and from CMM in that it targets hardware deployment rather than process maturity. First, TRL assigns a single readiness score on a nine-point scale based on whether a technology has been demonstrated in a relevant environment; it does not decompose readiness into governance, durability, or integration dimensions that determine whether a sensing system can function as a persistent node in a construction information management architecture. A garment system can reach TRL 5 while still having unresolved laundering durability, no data governance framework, and no interface with site management systems. The deployment-maturity framework scores these separately, making it possible to identify the specific bottleneck rather than assigning a single readiness level. Second, TRL was designed for defense and aerospace procurement; this framework specifically addresses construction informatics deployment by including information-system integration and worker acceptance as first-class dimensions.

Applying the framework to all seven field or field-simulated S2 records, the subset most relevant to deployment readiness assessment, demonstrates its diagnostic function across the broadest available operational evidence. To assess rating consistency, a second reviewer independently applied the framework to the same seven records. Agreement across all five dimensions for all seven records was 32/35 (91%), with three partial disagreements on the human/organizational acceptance dimension where worker feedback was ambiguously reported. The pattern is consistent across both raters: no S2 record achieves high ratings on all five dimensions simultaneously. Technical performance is where current systems are strongest; validation maturity, durability, and system integration are the consistent gaps. The framework builds on the Technology Readiness Level (TRL) literature originating in NASA and ESA systems engineering and adapted for construction technology assessment. It extends TRL by incorporating sociotechnical systems theory, treating readiness as a multidimensional construct involving not only technical maturity but also organizational capacity, human acceptance, governance readiness, durability under operational conditions, and system integration capability. This multidimensional framing reflects the insight that a system may achieve high technical performance (TRL 4) while

remaining far from deployment readiness because of non-technical barriers in governance, durability, or integration dimensions.

Operational durability is the dimension most consistently absent from the corpus. Among 63 empirical records, durability or washability testing was explicitly reported in a minority of studies. Zhang et al. [23] is one of the few studies to specifically address this dimension, reporting signal degradation approaching 30% after 25 industrial wash cycles. Battery endurance ranged widely across records reporting this variable; most systems cannot sustain uninterrupted monitoring across a full construction shift without recharging. These are not refinement problems; they are basic prerequisites for garments intended as persistent sensing nodes in a construction IT infrastructure. Human and organizational acceptance, including worker comfort, privacy concerns, and trust, functions as a mediating factor between technological feasibility and adoption. Systems integration—interoperability with BIM models, safety dashboards, or digital twins—remains underdeveloped in most current studies.

Smart garment maturity should be evaluated as a multidimensional construct, where sensing performance, validation realism, durability, human acceptance, and integration each represent a distinct deployment barrier rather than an isolated technical metric. Weakness in any single dimension constrains field adoption despite strong results in others. This framework reframes the research agenda: the field does not need more laboratory prototypes achieving marginal accuracy improvements; it needs purpose-designed studies that address the five dimensions jointly.

Figure 6 presents the deployment-maturity scorecard for the seven field or field-simulated records, while Table 7b provides the detailed record-level ratings and Table 7a defines the scoring rubric used to assign high, partial, low, and NR ratings.

Record	Technical Performance	Validation Maturity	Operational Durability	Human/Org. Acceptance	System Integration
Rashidi et al. 2025	High	High	NR	NR	Low
Edirisinghe & G. 2025	High	High	NR	Partial	Partial
Edirisinghe & G. 2026	High	High	NR	Partial	Partial
Jebelli et al. 2018	High	High	NR	Partial	Low
Keränen et al. 2015	Partial	High	NR	NR	Low
Ray & Teizer 2012	High	High	NR	NR	Partial
Akhavian & Behzadan 2018	High	Partial	NR	NR	Low

Figure 6. Deployment-maturity scorecard for seven field or field-simulated smart-garment records. Ratings: high = dimension fully addressed; partial = partially addressed; low = weakly addressed; NR = not reported. Source: Table 7a (operational rubric) and Table 7 (individual record data). Colors show the criticality. Data were synthesized from references [18,24,27–32].

The illustrative application of this framework to seven field or field-simulated S2 records is described in Section 5.5. The framework is conceptual; scores are not quantitatively derived from S2 but are based on whether each dimension was empirically addressed in the respective study. Smart shirts designed specifically for real-time workplace risk prevention and ergonomic monitoring demonstrate how garment-integrated sensing can be built for deployment from the outset [24].

Table 7. (**a**) Operational scoring rubric for the deployment-maturity framework dimensions. (**b**) Deployment-maturity framework applied to seven field or field-simulated S2 records. Ratings are qualitative (high/partial/low/NR = not reported) based on evidence reported in S2; the framework is proposed and illustratively applied, not statistically validated. Low and NR are distinct: low indicates the dimension was addressed but the evidence reported was weak, minimal, or unfavorable (e.g., a standalone system with limited integration), while NR indicates the source record did not report information relevant to that dimension at all, so no judgment, favorable or unfavorable, could be made.

(a)

Dimension	High	Partial	Low	NR
Technical Performance	Quantitative metric (accuracy, F1, AUC, RMSE) reported with acceptable validation basis	Feasibility or performance trend reported with limited quantitative metric	Weak, unstable, or inadequate performance reported	Performance not reported
Validation Maturity	Real construction site or realistic field validation with construction tasks	Field-simulated or semi-controlled task environment comparable to construction	Laboratory-only validation	Validation context not reported
Operational Durability	Washability, durability, or power autonomy tested under repeated or full-shift conditions	Durability, washability, or power discussed but incompletely tested	Durability limitation reported without mitigation	Not reported
Human/Org. Acceptance	Worker comfort, usability, or trust assessed with participant feedback	Worker use described but no systematic acceptance evaluation conducted	Comfort or adoption barrier reported	Not reported
System Integration	Connected to BIM, digital twin, safety dashboard, or site management system	IoT/cloud/platform connection demonstrated but not integrated into site workflow	Standalone prototype with no integration pathway	Not reported

(b)

Study	Tech. Performance	Validation Maturity	Oper. Durability	Human/Org. Acceptance	System Integration
Rashidi et al. [18]—multi-sensor safety vest; F1 = 0.88; field-validated on construction site	High	High	NR	NR	Low (standalone vest)
Edirisinghe and Gunathilake [29]—IoT heat-stress smart vest; field-validated; construction site	High	High	NR	Partial (worker use described)	Partial (IoT platform)
Edirisinghe and Gunathilake [27]—IoT heat-stress system; field/applied; construction site	High	High	NR	Partial (worker use described)	Partial (IoT platform)
Jebelli et al. [32]—vest IMU harness; EEG/GSR/HRV; AUC = 0.87; field construction site	High	High	NR	Partial (voluntary participant use)	Low (standalone system)
Keränen et al. [30]—wearable smart suit; IMU; ML fatigue trend; field construction site	Partial (trend only, no quantified accuracy)	High	NR	NR	Low (standalone)
Ray and Teizer [31]—safety vest UWB; position error ~20 cm; field construction site	High	High	NR	NR	Partial (site positioning system)
Akhavian and Behzadan [28]—vest-mounted IMU; accuracy = 89%; field-simulated	High	Partial (simulated, not real site)	NR	NR	Low (standalone)

5.6. Research Gaps and Future Priorities

Six specific priorities emerge from the corpus evidence. First, full-shift field validation: of 63 empirical records, only 7 were field or field-simulated, of which 6 reached TRL 5, and

none reported full-shift testing on a real construction site alongside standard work duties. Future studies should report performance, wear experience, and maintenance demands over complete shifts, not only controlled laboratory sessions. Second, standardized benchmarking: there is no shared definition of minimum sensitivity, maximum acceptable latency, or common task protocol for fall detection, ergonomic posture classification, or heat-stress monitoring in construction. Domain-specific minimum thresholds and shared evaluation protocols are needed to enable cross-study comparison. Third, systematic durability testing: laundering protocols for construction smart PPE should specify industrial versus domestic wash cycles, minimum cycle counts, and performance re-evaluation requirements. Studies should report performance before and after repeated wash cycles, not only signal integrity [23]. Fourth, data governance frameworks: empirical evidence on whether data-minimization, purpose-limitation, and worker-transparency policies materially affect adoption rates is absent from the corpus [37,40]. Governance research is needed alongside technical validation. Fifth, BIM and safety dashboard integration: only a small number of corpus records interfaced garment data streams with construction information management systems. Sixth, sustainability impact assessment: lifecycle and environmental impact reporting (battery disposal, e-waste, conductive-textile end-of-life) is almost entirely absent from the corpus, with only 11 of 63 empirical records (17%) reporting any lifecycle-relevant sustainability variable; future smart-garment validation studies should treat sustainability reporting as a standard requirement rather than an optional addition.

5.7. Limitations

This review has eight limitations that should be considered when interpreting findings. First, the search was restricted to English-language publications, which may exclude relevant studies published in other languages; the extent of this geographic coverage bias cannot be quantified. Second, the review represents a single-date snapshot (search executed 31 December 2025), and studies published after that date are not captured. Third, S2 extraction used free-text fields for garment type, sensing modality, and computational framework, which limits normalized cross-record counting; architecture statistics are therefore described qualitatively. Fourth, no empirical records were rated low quality (all 63 scored 6–9/12), making low-quality exclusion sensitivity analysis inapplicable. Fifth, the deployment-maturity framework ratings are qualitative and assessor-interpreted; they are not quantitatively derived from S2 scores and should be treated as diagnostic rather than evaluative instruments. Sixth, gray literature, including technical reports, white papers, patents, vendor documentation, and unpublished industry pilots, was excluded because the review focused on peer-reviewed journal articles and indexed conference proceedings to maintain quality control and reproducibility. This exclusion may underestimate industry-level development, because commercial or patent-stage smart-garment systems may be more advanced than the academic literature indicates. Seventh, the corpus is likely affected by publication bias toward successful or partially successful systems. Failed deployments, abandoned prototypes, negative worker-acceptance results, and systems that performed poorly in the field are less likely to appear in peer-reviewed literature. As a result, this review may systematically overestimate technological readiness and underestimate the practical difficulty of sustained construction deployment. Eighth, 45 of the 63 empirical records (71%) are transferable evidence from non-construction domains rather than direct construction validation; conclusions about deployment readiness, sensor-fusion advantages, and validation-context effects therefore depend substantially on the assumption that these transferable records generalize to construction settings, an assumption that is plausible but not independently verified for most records.

6. Conclusions

This review extends and reframes findings from prior wearable-sensing research across three areas, with direct implications for the sustainable development of construction safety practice.

Prior reviews established that IMU-based sensing is feasible for ergonomic and fall monitoring, that physiological sensing faces signal stability challenges under construction conditions, and that privacy concerns consistently limit adoption. These findings are well documented in prior narrative and scoping reviews. The 63 empirical records in this corpus strengthen their evidentiary basis: garment-integrated IMU sensing has reached prototype-to-pilot maturity (TRL 4–5) across ergonomic and fatigue domains, with localization evidenced by a single verified record, and multimodal configurations often reported stronger performance than single-modality systems in controlled evaluations. This pattern should be interpreted cautiously: 45 of the 63 empirical records are transferable evidence drawn from non-construction domains (healthcare, sports, rehabilitation) rather than direct construction validation, so apparent performance advantages may partly reflect the maturity of the source domain rather than construction-specific readiness. Critically, the persistent gap between laboratory performance and field readiness documented here is not merely a technical limitation; it is a sustainability barrier. Construction worker injuries and fatalities impose cascading social and economic costs, including medical treatment, lost productivity, workforce attrition, and long-term disability, that undermine the social and economic dimensions of sustainable development. Closing the lab-to-field gap is therefore a prerequisite for smart garments to deliver on their potential as sustainable safety infrastructure.

Building on prior findings, this review makes four analytical contributions. First, the tiered corpus classification, separating 18 construction-direct records, 45 transferable records, and 13 contextual sources, makes explicit which evidence supports which inferential claims about construction deployment; prior reviews did not make this distinction. Second, systematic validation-context stratification reveals a consistent lab-to-field gap: only 7 of 63 empirical records were field or field-simulated, of which 6 reached TRL 5, yet high-performance figures in the literature are predominantly laboratory results. Third, an explicit transferability assessment for records from healthcare, occupational safety, and sports provides a principled basis for including non-construction evidence while preventing conflation with construction-direct findings. Fourth, the deployment-maturity framework diagnoses which specific dimension, among technical performance, validation maturity, durability, human and organizational acceptance, or system integration, is limiting deployment for any given system type. Applied to seven field or field-simulated S2 records (Table 7), the framework suggests that technical performance is often not the primary limiting dimension among the systems with field or field-simulated evidence; validation maturity, durability, and system integration appear to be the more consistent gaps. Because this pattern is drawn from only seven field or field-simulated records, it should be read as a preliminary signal rather than a generalizable conclusion.

Returning to the four research questions posed in the Introduction, RQ1 is answered by the three-wave publication analysis, which shows acceleration from fewer than five records per year in Wave 2 to approximately seven per year in Wave 3, with a concurrent shift toward edge-AI architectures and multimodal sensing configurations. RQ2 is answered by validation-context stratification, which indicates that laboratory results are generally higher than field or field-simulated results, suggesting that high-accuracy figures widely cited in the literature are largely controlled-experiment results and should not be interpreted as operational benchmarks. RQ3 is answered by the deployment barrier synthesis in Sections 5.1–5.3, which identifies durability, data governance, and system integration as

the consistent cross-tier gaps, not sensing accuracy. RQ4 is answered by the framework application in Table 7, where no record achieves high ratings across all five dimensions simultaneously, and where technical performance is the dimension closest to readiness while validation maturity, durability, and integration remain the persistent bottlenecks.

The framework's most important implication is that the field may have been systematically misattributing its readiness gap. When high laboratory accuracy is treated as evidence of deployment readiness, the actual bottlenecks—validation maturity, operational durability, and system integration—remain invisible and uninvestigated. The deployment-maturity framework makes those bottlenecks explicit and assessable, redirecting research investment toward the dimensions that actually constrain field adoption. From a sustainability standpoint, this misattribution has real costs: investment continues to flow toward marginal laboratory accuracy improvements while the durability, governance, and integration gaps that prevent adoption at construction scale remain unaddressed, and preventable injuries continue to occur.

The data show that the main pathway to stronger and more transferable conclusions is not additional prototype variety, but more consistent evaluation practice, addressed through the six research priorities detailed in Section 5.6 (full-shift field validation, standardized benchmarking, durability testing, data governance, systems integration, and sustainability impact assessment). Equity-focused deployment studies are also needed to examine whether adoption benefits reach all workforce demographics, including migrant workers, non-English-speaking workers, and workers in small firms, consistent with the Sustainable Development Goal 8 equity concern discussed in Section 5.3.

For practitioners, safety managers, contractors, or PPE procurement officers considering a smart garment pilot, the deployment-maturity framework translates into four practical screening criteria, each mapped to a deployment stage. Before procurement: Confirm the system has been field-validated, not only laboratory-validated, and that full-shift battery endurance has been demonstrated; these two criteria alone eliminate most currently published systems from immediate operational readiness. Before deployment: Verify the system has been tested through the site's standard laundering cycle and that performance data were collected after wash cycling, not only from fresh garments. Before worker rollout: Establish a written data governance policy specifying that biometric data are used exclusively for safety decisions and not for productivity tracking or disciplinary purposes. Before scaling: Verify that alert data can be routed into existing site safety dashboards rather than operating as a standalone device. A garment that meets all four criteria is likely operationally ready; one that fails any criterion should be treated as a pilot requiring structured evaluation before broader deployment.

Beyond immediate deployment decisions, this review underscores a broader sustainability imperative. Construction worker injury and fatality remain among the most persistent barriers to socially sustainable development in the built environment industry. Smart garments, deployed responsibly and evaluated rigorously across all five maturity dimensions, represent a promising pathway toward continuous, worker-level safety monitoring that could meaningfully reduce preventable harm at construction scale. Realizing this potential, however, requires a shift in research priorities, from laboratory accuracy optimization toward field validation, lifecycle durability, equitable adoption, and governance frameworks that protect workers rather than surveil them. These are not merely engineering challenges; they are sustainability challenges, and addressing them is essential for making the construction workforce a safer, more equitable, and more sustainable foundation for the built environment.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18168359/s1, Supplementary File S1: Search, Evidence, and PRISMA Documentation Workbook. Supplementary File S1 is a single Excel workbook containing seven sheets (S1 through S7), each described in the captions below. This workbook includes seven sheets documenting the database search strategy, screening process, evidence extraction dataset, quality appraisal rubric, domain-level quality scores, TRL assignments, primary hazard-domain classification, normalized validation context, PRISMA pathway estimates, verification notes, and performance-summary documentation. The workbook contains the 76-record classified corpus, including the 63 empirical benchmark records used for quality scoring, TRL classification, hazard-domain analysis, Figure 5, Table 5, and Figure 6. Every corpus record documented in the workbook includes full citation metadata and a DOI or stable source URL. A subset of additional corpus records documented in the workbook but not otherwise cited elsewhere in this article are referenced here as [43–94]. Supplementary File S1 Sheet Captions: Sheet S1: Overview and manuscript metadata for the classified corpus. Sheet S2: Evidence Table—full 76-record extraction dataset with author, year, corpus role, garment type, sensor modality, hazard domain, validation context, quality score, TRL, and DOI/URL for each record. Sheet S3: Quality Summary—corpus role, quality class, and domain-level quality score distributions. Sheet S4: Codebook—variable definitions and decision rules used to populate the Evidence Table. Sheet S5: PRISMA Screening—database search and screening counts underlying the PRISMA 2020 flow diagram. Sheet S6: Verification Notes—source-verification status and treatment of contextual/broader records. Sheet S7: Performance Summary (IQR)—median, interquartile range, and range of reported performance by hazard domain × validation context.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Full Term
AUC	Area Under the Curve
CMM	Capability Maturity Model
CNN	Convolutional Neural Network
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
GNSS	Global Navigation Satellite System
GSR	Galvanic Skin Response
HR	Heart Rate
HRV	Heart Rate Variability
ICC	Intraclass Correlation Coefficient
IMU	Inertial Measurement Unit
IQR	Interquartile Range
LSTM	Long Short-Term Memory
ML	Machine Learning
NR	Not Reported (Table 7 only)

PCB	Printed Circuit Board
PICOS	Population, Intervention, Comparator, Outcome, Study Design
PPE	Personal Protective Equipment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal
sEMG	Surface Electromyogram
TRL	Technology Readiness Level
UWB	Ultra-Wideband

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