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Wearable Assistive Devices for Proactive Management of Socio-Technical System Risks: A Systematic Review and Hierarchical Impact Model

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ABSTRACT

This review synthesizes evidence from 176 peer-reviewed publications (2010–2025) to examine the role of wearable assistive technologies in supporting proactive risk management within high-risk socio-technical systems. The study was conducted in accordance with PRISMA 2020 guidelines, applying a thematic synthesis approach alongside a structured quality assessment. Evidence consistently demonstrates significant reductions in biomechanical precursors of risk (15–45% muscle activity reduction), while effects on cognitive workload and situational awareness remain context-dependent. Direct reductions in lagging injury indicators are weakly evidenced, reflecting the hierarchical nature of accident causation. We introduce the hierarchical impact model of wearable assistive devices (HIM-WAD), conceptualizing WADs as dynamic, human-integrated safety enablers that primarily act on physiological and behavioral precursors. Practical implications emphasize human-centered design, transparent data governance, and mitigation of risk compensation. WADs should be positioned not as standalone protective tools but as cross-level safety observability systems enabling the transition from reactive Safety-I to proactive Safety-II governance.

1. INTRODUCTION

Modern industrial environments are increasingly shaped by complex interactions between human operators, technological systems, and organizational structures, which contribute to emerging safety challenges [1, 2].

Despite advances in safety management, work-related incidents persist, often stemming not from isolated equipment failures but from the dynamic interplay of human, technical, and organizational factors [1, 3]—a reality that traditional static risk assessment methods struggle to address [2, 4].

Conventional approaches (e.g., hazard studies, checklists, quantitative risk analysis) rely on fixed assumptions about exposure and human reliability [5, 6], failing to capture real-time fluctuations in workers' physical and functional states. Fatigue, biomechanical load, and postural instability evolve during work shifts and are recognized as critical precursors to errors, near-misses, and musculoskeletal disorders. This creates a systematic gap between formal risk assessments and actual hazard mechanisms in daily practice [3, 7].

This reactive approach is consistent with the Safety-I paradigm, which focuses on preventing adverse outcomes. In contrast, the Safety-II perspective emphasizes the need to monitor and manage variability in everyday system performance [8]. Bridging this gap requires tools capable of continuous monitoring and translating physiological data into actionable safety intelligence.

Wearable assistive devices (WADs) have emerged as a promising response. Unlike conventional Personal Protective Equipment (PPE), WADs provide active support and real-time monitoring, reducing biomechanical strain and generating leading risk indicators [9, 10]. Positioned between PPE and engineering controls, they enhance individual capacity while feeding data into safety management systems.

However, evidence on WADs' role in proactive risk management remains fragmented across disciplines. Studies often focus on isolated biomechanical outcomes and lack system-level integration [9, 10]. Critical challenges – user acceptance, behavioral adaptation, data interoperability – remain underexplored, limiting WADs' preventive potential.

Although previous systematic reviews have synthesized biomechanical evidence [9, 10] and examined technology acceptance factors [11, 12], several important gaps remain. First, there is still no comprehensive cross-level framework that integrates physiological, behavioral, and operational effects with overall outcomes. Second, leading indicators based on wearable data remain insufficiently developed and validated. Third, there is a lack of longitudinal research assessing the sustainability of effects and their integration into organizational practice.

The literature on WADs can be broadly organized into three disciplinary streams. The first stream, rooted in ergonomics researches [13-20] focuses on biomechanical efficacy, including reductions in muscle activity, postural control, and fatigue, typically assessed using laboratory-based electromyograph (EMG) and motion capture techniques.

The second stream, emerging from safety engineering [1, 4, 5, 21-24], examines risk assessment frameworks, leading indicators, and the integration of WADs into safety management systems.

The third stream, grounded in human factors and technology acceptance research [4, 11, 25-31], explores user perceptions, adoption barriers, and organizational influences on implementation.

Despite advances within each stream, integration across these domains remains limited. This fragmentation constrains the development of comprehensive, system-level approaches to WAD implementation—a gap this work aims to address.

The present study examines the current state of research on WADs in occupational safety and identifies key gaps. Specifically, it aims to:

1. Analyze WADs' effects on biomechanical and cognitive risk precursors.
2. Assess their contribution to dynamic human factor monitoring.
3. Identify implementation challenges (e.g., risk compensation).
4. Formulate evidence-based recommendations for integrating WADs into OSH systems to enable proactive risk governance.

The originality lies not in identifying new biomechanical effects, but in integrating fragmented findings into a unified hierarchical model (impact model of wearable assistive devices (HIM-WAD)) linking physiological, behavioral, operational, and outcome levels of risk formation.

2. METHODS

2.1 Study design and reporting framework

This study was designed as a systematic review of peer-reviewed literature to evaluate the role of WADs in occupational and technogenic risk management.

The design and reporting of this review were guided by the PRISMA 2020 framework [32], focusing on clear reporting of the search strategy, study selection, and data synthesis.

Due to variation in study designs, outcome measures, and application contexts, a qualitative synthesis approach was adopted, and no meta-analysis was performed.

Although a review protocol was not formally registered (e.g., in PROSPERO or OSF), the study followed predefined eligibility criteria, a structured search strategy, and transparent reporting of the selection and synthesis processes.

2.2 Research question

The review was guided by the following research question: What evidence exists regarding the effectiveness of WADs in enabling proactive management of technogenic and occupational risks, and what are the practical implications for occupational safety and health systems?

2.3 Data sources and search strategy

Scopus, Web of Science, and PubMed were searched (2010–2025) using terms for: (1) wearable technology ("exoskeleton," "smart PPE," "wearable sensor"); (2) safety context ("occupational safety," "risk management," "technogenic risk"); and (3) human factors ("ergonomic," "worker fatigue," "biomechanical load").

Of 2,150 initial records, 480 duplicates were removed. After screening 1,620 titles/abstracts and assessing 440 full texts, 176 studies met inclusion criteria (Figure 1).

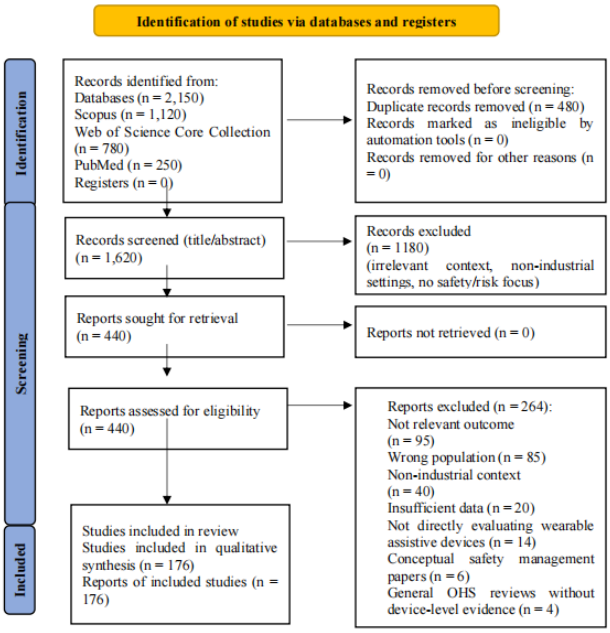

Figure 1. PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in the qualitative synthesis

2.4 Eligibility criteria

Studies were selected based on predefined inclusion and exclusion criteria (Table 1).

During full-text screening, conceptually relevant but non-empirical or non-device-specific publications were excluded to ensure methodological consistency with inclusion criteria. This refinement strengthened internal validity, restricting the evidence base to studies directly evaluating WADs in occupational safety contexts. The final qualitative synthesis included 176 studies (Figure 1).

Table 1. Eligibility criteria for study selection

Criterion	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles	Conference abstracts, theses, book chapters, non-peer-reviewed reports
Language	English	Non-English publications
Population/Context	Industrial or high-risk occupational settings	Clinical rehabilitation, sports, or military applications exclusively
Intervention	Wearable assistive device evaluation (active/passive support, with/without sensors)	Standard Personal Protective Equipment (PPE) without assistive or monitoring functions
Outcome	Safety, risk perception, human performance, biomechanical load, leading/lagging indicators	No link to occupational risk or safety management
Study Design	Empirical studies, field trials, longitudinal, reviews, methodological papers	Purely theoretical or speculative commentaries without data

2.5 Study selection process

The study selection process is summarized in the PRISMA 2020 flow diagram (Figure 1). After duplicate records were removed, titles and abstracts were screened against the predefined eligibility criteria. Articles considered potentially relevant were subsequently assessed through full-text review.

Study selection was conducted independently by two authors (A.A. and M.A.). Any discrepancies were addressed through discussion and, if required, by involving a third author (M.N.). No automated tools were employed; all decisions relied on the predefined eligibility criteria (Table 1).

Following this multi-stage screening procedure, the final set of studies was identified and included in the qualitative synthesis.

2.6 Data extraction and synthesis

A standardized form extracted author(s), year, design, context, device type, outcomes, and key findings from each study.

Given the substantial heterogeneity across studies in design types, measurement approaches (including EMG, IMUs (inertial measurement units), and subjective ratings), and outcome definitions, a quantitative meta-analysis was not feasible. Many studies reported qualitative findings or used non-comparable metrics, precluding statistical pooling.

A thematic synthesis approach was therefore adopted [25], conducted iteratively in four stages:

(1) Familiarization: In-depth reading of all 176 studies to understand contexts, methods, and findings.
(2) Inductive coding: Systematic identification of key concepts and findings, assigning descriptive codes (e.g., "EMG reduction in upper limbs," "user resistance due to discomfort").
(3) Theme development: Codes were clustered into broader descriptive themes, including Biomechanical Load Reduction, WADs as Sources of Leading Indicators, and Human-Technology-Organization Integration Factors.
(4) Analytical synthesis: Themes were interpreted to generate higher-order analytical concepts, culminating in the HIM-WAD (Figure 2).

Coding followed an inductive approach without predefined categories. Initial codes were generated from the data and iteratively grouped into descriptive sub-themes and higher-level analytical themes. Two authors (A.A. and M.A.) independently coded the same subset of 20 studies. Disagreements were resolved through discussion. Coding was managed using Microsoft Excel, with codes organized thematically. The full coding framework, including examples of how raw codes were grouped into descriptive sub-themes, analytical themes, and HIM-WAD levels, is illustrated in Supplementary Material S3.

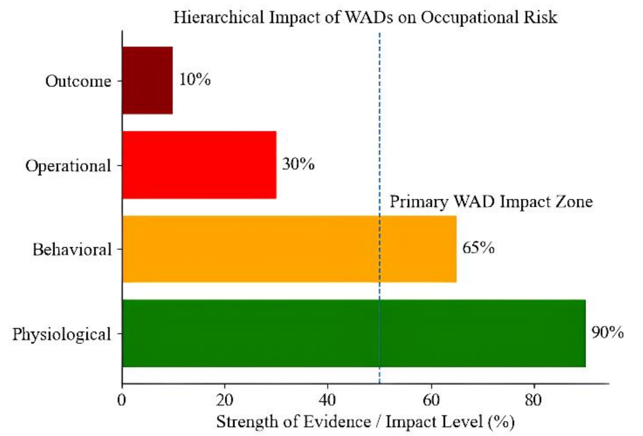

Figure 2. Hierarchical impact of wearable assistive devices (WADs) on occupational risk formation
Note: Bars show strongest evidence at physiological level, diminishing at operational and outcome levels

This framework integrated insights from ergonomics, safety engineering, and human-computer interaction. To ensure transparency, Supplementary Material S3 illustrates the analytical pathway from raw codes to conceptual abstraction, documenting how representative codes informed each theme and hierarchical level.

2.7 Risk of bias and quality assessment

A two-stage assessment strategy evaluated: (1) risk of bias in the review process, and (2) methodological quality of included primary studies.

Review process bias was assessed using the ROBIS tool [33], covering eligibility criteria, study identification, data collection, and synthesis. The assessment confirmed low concern regarding bias in the review methodology.

Table 2. Summary of methodological appraisal for included studies by primary design category

Study Category	Count (n)	Appraisal Focus & Common Considerations	Implications for Evidence Strength
Laboratory experiments	80	Focus: High internal validity for measuring direct biomechanical effects. Considerations: Lack of participant blinding; limited ecological validity; short task duration.	Strong for proof-of-concept and causal efficacy. Moderate/Limited for real-world generalization.
Short-term field studies / pilots	64	Focus: Initial feasibility, usability, immediate effects. Considerations: Often no control group; novelty/Hawthorne effect; <3 months observation.	Moderate for initial acceptance and short-term benefit. Limited for sustained adoption and organizational impact.
Longitudinal field studies (≥12 wks.) & RCTs	24	Focus: Long-term efficacy, user adaptation, work integration. Considerations: Limited number of studies; small sample sizes; heterogeneous designs.	High for sustainable use, compensatory behaviors, and practical implementation.
Systematic & narrative reviews	8	Focus: Evidence synthesis and conceptual model development. Considerations: Variable quality of source reviews.	Variable. Used for contextualization and framework development.
Total included studies	176		

Note: RCT = Randomized Controlled Trial. Appraisal outcomes informed evidence weighting in the thematic synthesis and limitations discussion

Primary study quality was evaluated using design-specific tools due to substantial heterogeneity:

- RoB 2 for randomized controlled trials
- ROBINS-I for non-randomized and longitudinal field studies
- MMAT (2018) for laboratory experiments, short-term field studies, case studies, and mixed-method evaluations
- JBI checklists for observational studies and pilot evaluations
- AMSTAR 2 and JBI Systematic Review Checklist for reviews

These tools addressed allocation, outcome measurement, confounding, and analytical rigor. Quality appraisal outcomes informed evidence weighting in the thematic synthesis and limitations discussion. Table 2 summarizes results by study category.

This two-stage approach (ROBIS for review process + design-adapted tools for primary studies) ensured transparent, rigorous evaluation. Overall quality ratings for each study and summary distributions across tools (RoB 2, ROBINS-I, MMAT, AMSTAR 2) are provided in Supplementary Material S2. Most studies showed moderate quality/risk of bias; fewer were high quality or serious/critical risk.

3. RESULTS

3.1 Overview of included studies

From 2150 initial records, 176 studies met inclusion criteria. Publication activity increased markedly after 2016. Study designs included laboratory experiments (41%), short-term field studies (34%), longitudinal field studies (15%), and reviews (10%) (Table 3). Substantial heterogeneity in metrics and contexts supported thematic synthesis over meta-analysis.

The characteristics of all included studies are summarized in Supplementary Material S1, which provides complete bibliographic details and study types for each of the 176 records.

Table 3. Distribution of included studies by research design

Study Type	Proportion (%)	Primary Focus
Laboratory-based experimental	41%	Biomechanics, kinematics, physiological load under controlled conditions.
Short-term field studies	34%	Usability, immediate effects, and feasibility in real operational settings.
Long-term field studies (≥12 weeks)	15%	Technology adoption, longitudinal effects, integration into work practices.
Review and methodological papers	10%	Conceptual models, frameworks, and synthesis of existing evidence.

3.2 Biomechanical and physiological effects: Reduction of risk precursors

The analysis shows that WADs are associated with measurable changes in biomechanical and physiological factors, as well as cognitive aspects relevant to occupational risk. WADs reduced biomechanical load, including muscle activity, during manual tasks. Muscle activity reductions of 15% -45% were reported across shoulder and back regions [7, 13, 34], consistent with prior reviews [16, 18]. Inter-individual variability (SD 4%–12% MVC) reflected task and device differences [35-37].

Task-specific findings included:

- Overhead lifting: 4.1%–15.7% MVC reduction (up to 49%) [36]
- Manufacturing: 21.6% (anterior deltoid) and 13.6% (medial deltoid) reduction [13]
- Shoulder postures: 9%–24% reduction across abduction angles [38]
- Repetitive movements: reduced muscle coactivation [17]

WADs also improved postural control, reducing trunk flexion and joint angular velocities during lifting and overhead tasks [15].

Cognitive effects were variable. Most studies reported reduced subjective cognitive workload due to decreased physical strain [37, 39], though initial adaptation phases showed temporary increases in cognitive load from device awareness or feedback processing [15, 36]. Situational awareness could be enhanced by intuitive feedback [39-41] or degraded by restrictive designs [42, 43].

Across industry contexts, the magnitude of biomechanical benefit varied systematically. Manufacturing settings demonstrated relatively consistent reductions in muscle activity (13.6–21.6%) [13]. In contrast, construction applications exhibited greater variability (9–49% reduction) [36, 38]. Logistics and warehousing contexts showed intermediate effects (15–35% reduction) [35], with longitudinal evidence indicating sustained but gradually diminishing benefits over a 24-week period [35].

Table 4 summarizes the range of biomechanical effect sizes and cognitive trends reported across the diverse tasks, devices, and protocols in the included studies.

Table 4. Summary of reported effects from wearable assistive devices (WADs) on risk precursors

Outcome Metric	Reported Effect Range (or Trend)	Primary Risk Link	Representative Studies
Muscle activity (EMG)	15%–45% reduction	Decreased fatigue accumulation, lower risk of muscular strain	[13, 15, 36]
Cumulative biomechanical load	10%–35% reduction	Reduced risk of overuse injuries and musculoskeletal disorders	[13, 14]
Subjective fatigue ratings	10%–30% reduction	Improved functional state and sustained performance capacity	[13, 35]
Cognitive load (subjective)	Variable: reduction in most cases, increase during initial adaptation	Influences error rates, attention to hazards, and procedural compliance	[13, 15, 17, 36, 39]
Situational awareness	Context-dependent: can be enhanced or degraded	Critical for proactive hazard recognition and avoidance	[41, 43]

Note: Ranges for biomechanical outcomes are illustrative of the literature. Cognitive and awareness outcomes are described qualitatively due to heterogeneous measurement approaches. EMG = Electromyograph

3.3 Wearable devices as a source of leading indicators for dynamic risk assessment

The literature identifies WADs' capacity to generate leading safety indicators – continuous, objective data streams reflecting pre-incident risk states, unlike traditional lagging metrics (e.g., injury rates). The literature identifies validated proxy indicators from WAD data (Table 5). Studies show prolonged non-neutral postures, elevated muscle activity, and cumulative exposure time serve as early risk signals [44].

Table 5. Examples of leading risk indicators generated by wearable assistive devices (WADs)

Leading Indicator	Data Source	Risk Interpretation
Frequency of hazardous postures	Inertial measurement units (IMUs), kinematics	Elevated probability of acute injury or chronic musculoskeletal disorder
Cumulative lumbar load / force	Force sensors, kinetic models	Risk of low-back pain and fatigue-related error
Gait instability / sway metrics	Accelerometers, gyroscopes	Increased risk of slips, trips, and falls
Event rate of automated warnings	Device interaction logs	Indicator of procedural non-compliance or high-risk task phases

A pilot study reported reductions in upper-limb biomechanical load during industrial manufacturing tasks when using a passive exoskeleton [13]. Experimental evaluations similarly demonstrated reduced muscular activity during static upper-limb tasks with the use of passive exoskeletons [45].

Strong evidence supports WAD effects on physiological and behavioral precursors (Levels 1–2, Figure 2). However, direct evidence linking WAD use to reduced lagging indicators (Total Recordable Injury Rate (TRIR), Lost-Time Injury Frequency Rate (LTIFR)) remains limited and indirect.

4. DISCUSSION

4.1 Wearable assistive devices as enablers of proactive socio-technical risk governance

Drawing on evidence from 176 studies, the present study frames WADs not simply as incremental extensions of traditional PPE, but as active, human-centered tools embedded within broader socio-technical safety systems. Unlike passive barriers, WADs generate continuous data on physiological and behavioral states, facilitating a shift from reactive Safety-I – focused on lagging indicators and retrospective analysis – towards proactive Safety-II governance. By monitoring real-time fatigue, biomechanical load, and posture, WADs operationalize the Safety-II principle of managing performance variability before adverse outcomes occur.

WADs extend the traditional hierarchy of controls. Although worn at the individual level, they provide active assistance and generate data that can inform higher-level engineering and administrative decisions.

In this sense, WADs can be viewed as enabling technologies that improve system observability across different control levels. This shifts the role of the worker from a static risk factor to a dynamic element within a socio-technical system.

The marked increase in publication activity after 2016 likely reflects growing interest in Industry 4.0 and data-driven safety approaches [46].

4.2 Interpreting the hierarchical impact model: A framework for realistic expectations

The evidence reveals a distinct gradient: robust physiological effects but limited direct impact on lagging injury rates. This reflects the multi-layered nature of accident causation in socio-technical systems, not a technological shortcoming. Improvements at the individual level must propagate through behavioral and organizational layers before influencing high-level statistics.

To formalize this, we introduce the HIM-WAD, conceptualizing a four-level cascade:

- Level 1 – Physiological precursors: Direct effects on muscle activity, joint loading, fatigue, and neuromuscular coordination.
- Level 2 – Behavioral precursors: Changes in posture, movement quality, and ergonomic compliance.
- Level 3 – Operational safety indicators: Observable changes in near-miss frequency, unsafe acts, and ergonomic risk scores.
- Level 4 – Lagging safety outcomes: Ultimate effects on injury rates (TRIR, LTIFR) and compensation claims.

The HIM-WAD complements and extends established safety frameworks. Reason's Swiss Cheese model [13] conceptualizes accidents as the alignment of latent failures across defensive layers; HIM-WAD specifies how WADs act as active barriers at the physiological level (Level 1), reducing the likelihood of error precursors before they propagate. Rasmussen's risk management framework [2] describes safety as emerging from dynamic interactions across system levels; HIM-WAD operationalizes this by providing measurable indicators for each level – from individual muscle activity (Level 1) to organizational safety metrics (Level 4). Unlike linear causation models, HIM-WAD explicitly acknowledges diminishing controllability across levels and the mediating role of organizational factors (Omod) and temporal dynamics (Tlag).

For example, in a warehouse setting, a reduction in muscle activity (Level 1) and hazardous postures (Level 2) following WAD implementation can be monitored as leading indicators of improved safety performance, potentially predicting downstream reductions in near-miss events (Level 3) over time.

This variability across industry contexts may be explained by differences in task standardization, device-task alignment, and environmental conditions. These findings indicate that WAD effectiveness is context-dependent, with task standardization and device-task compatibility as key moderating factors.

To support practical application, Table 6 outlines indicative metrics, data sources, and evidence-informed thresholds for each HIM-WAD level. For example, at Level 1, a 10–15% reduction in EMG amplitude (%MVC) has been associated with delayed onset of muscle fatigue [37, 47], while trunk flexion exceeding 30° for more than 5% of working time has been linked to a 2.3-fold increase in MSD risk [14].

At Level 2, reductions in warning event rates (e.g., by ~20%) have been associated with corresponding decreases in near-miss frequency (~12%) [44]. At Level 3, decreases in near-miss rates have been shown to correlate with subsequent reductions in LTIFR ($R^2 = 0.47$), although this relationship is influenced by organizational and temporal factors [48].

These indicative thresholds may assist practitioners in setting measurable targets and evaluating WAD effectiveness using leading and intermediate indicators, without relying solely on lagging injury outcomes.

This dissociation reflects the hierarchical, multi-factorial nature of accident causation [1, 2], where individual-level improvements are mediated by organizational factors before influencing injury rates.

Collectively, the evidence indicates that WADs consistently reduce biomechanical load (typically in the 15%–50% range for key muscle groups), while their effects on cognitive factors are more nuanced and dependent on design and context [13, 16, 18].

The model posits diminishing direct controllability across levels. Strong biomechanical effects (Level 1) are well-evidenced, but their translation to organizational outcomes (Level 4) is mediated by broader system dynamics. Table 6 provides operational definitions and validation evidence for each hierarchical level, illustrating the specific metrics through which these effects can be observed and measured. This hierarchy explains why evaluating WADs solely by injury rates undervalues their preventive potential and contradicts Safety-II principles, which prioritize managing performance variability through leading indicators.

This cascade can be heuristically represented as ΔLevel4 ~ f (ΔLevel3, Omod, Tlag), where Omod represents organizational moderation (e.g., safety culture) and Tlag reflects temporal dynamics. Even substantial physiological gains may not reduce injury rates if behavioral translation is weak (e.g., risk compensation) or if organizational systems fail to act on leading indicators.

Occupational accidents result from interacting technical, procedural, and organizational failures across system levels [1, 4, 49]. WADs reinforce initial links by enhancing individual capacity, but translation to organizational outcomes depends on subsequent barriers. Evaluating WADs solely by injury rates undervalues their preventive potential [21] and contradicts Safety-II principles, which emphasize managing performance variability through leading indicators [8, 48].

Alternative explanations for limited injury evidence include: insufficient statistical power in short-term studies, behavioral risk compensation attenuating benefits, and possible load redistribution rather than elimination. These complexities underscore the need for rigorous longitudinal research.

Table 6. Operational definition of HIM-WAD

Level	Impact Domain	Operational Metrics	Data Source	Validation Evidence
Level 1	Physiological precursors	EMG amplitude (%MVC reduction), trunk flexion angle (°), cumulative lumbar load (Nm·s), heart rate (bpm)	EMG, IMU, wearable sensors, spirometry	10–15% MVC reduction = clinically meaningful fatigue delay [16, 17]; >30° trunk flexion associated with 2.3× increased MSD risk [14]
Level 2	Behavioral precursors	Hazardous posture frequency (events/hr), warning event rate, movement smoothness (jerk, m/s³)	Device logs, IMU, EHS observation	>5% working time in trunk flexion >30° = high MSD risk (OR 2.1–3.4) [3, 15]; 20% reduction in warning events correlates with 12% near-miss reduction [44]
Level 3	Operational safety indicators	Near-miss frequency (per 1000 hrs), unsafe act observations, ergonomic risk score (REBA, LUBA)	EHS records, safety audits, supervisor reports	1-log reduction in near-miss rate predictive of 0.3 – 0.5 log LTIFR reduction ($R^2 = 0.47$) [48]; Jakobsen 2025: 24-week RCT showed 41% near-miss reduction [35]
Level 4	Lagging safety outcomes	TRIR, LTIFR, MSD incidence, workers' compensation claims	Organizational safety statistics, national registries	RCT evidence only: Jakobsen 2025 (n = 48, 24 weeks) – no statistically significant LTIFR reduction, underpowered for injury endpoints [25-35]; epidemiological benchmarks exist but no RCT evidence for WADs

Note: Validation evidence draws from epidemiological exposure–response studies and WAD-specific longitudinal research identified in this present study. HIM-WAD = hierarchical impact model of wearable assistive devices; EMG = Electromyograph; IMU = inertial measurement units; MSD = musculoskeletal disorder; OR = odds ratio; RCT = randomized controlled trial; EHS = environment, health, and safety; REBA = Rapid Entire Body Assessment; LUBA = loading on the upper body assessment; TRIR = total recordable injury rate; LTRFR = lost-time injury frequency rate

4.2.1 Conceptual illustration of cascade dependencies

To complement the descriptive HIM-WAD framework, we heuristically illustrate conditional dependencies between hierarchical levels. The influence of WADs on lagging outcomes (Level 4) can be conceptualized as emerging from cumulative effects transmitted through preceding levels, moderated by organizational and temporal factors:

$$\Delta\text{Level4} \sim f(\Delta\text{Level3}, \text{Omod}, \text{Tlag}) \quad (1)$$

where:

- ΔLevel3 denotes observed changes in operational safety indicators (e.g., near-miss frequency, unsafe act rate)
- Omod represents contextual organizational moderation factors, including safety culture maturity, management commitment, reporting practices, and barrier effectiveness.
- Tlag reflects temporal dynamics, acknowledging that changes in leading indicators may require extended periods before observable effects appear in lagging outcomes.

$$\text{Level 1} \rightarrow \text{Level 2} \rightarrow \text{Level 3} \rightarrow \text{Level 4} \quad (2)$$

The cascade illustrates effect propagation across system layers, with likely attenuation at each stage due to intervening mediators. Even substantial physiological improvements may fail to reduce injury rates if:

(1) Translation to behavioral change is weak (e.g., risk compensation)
(2) Organizational systems fail to act on leading indicators
(3) Baseline injury rates are too low for detectable reduction (floor effect)

This conceptual illustration emphasizes that future research should examine mediation pathways and contextual moderators, not simplistic "WAD → injury reduction" hypotheses. Table 6 provides operational anchors for such investigations.

4.3 From data to decisions: Towards operational integration of wearable assistive devices into safety management systems

Translating WAD data into actionable intelligence requires a robust socio-technical architecture.

Illustrative application scenario: WADs in automotive assembly.

To demonstrate the practical application of the HIM-WAD model, consider a representative scenario from automotive assembly. A worker performs repetitive overhead fastening tasks on a production line. A passive upper-limb exoskeleton reduces anterior deltoid muscle activity by 21.6% and medial deltoid by 13.6% during standard operations [13]. This immediate physiological effect (Level 1) is associated with a reduction in hazardous postures, with the frequency of shoulder abduction >45° decreasing by approximately 30% over a shift (Level 2).

At the operational level, aggregated data from multiple workers can be used to generate heat maps of cumulative shoulder load across task types. Such analysis may reveal that specific tasks (e.g., left-side door panel installation) are associated with higher cumulative exposure than others. This information (Level 3) can support targeted ergonomic interventions, such as task rotation or tool redesign.

This example illustrates how the HIM-WAD cascade – from physiological change to behavioral adaptation and operational decision-making – can be applied in practice to support data-driven safety management.

Technically, this involves a four-layer data pipeline: (1) data acquisition (wearable sensors), (2) edge processing (on-device feedback), (3) fusion and analytics (integration with enterprise resource planning/ environment, health, and safety (ERP/EHS) platforms via open application programming interfaces (APIs)), and (4) decision support (dashboards for action).

Organizational integration is equally critical. Documented failures offer key lessons: the "surveillance backlash" case (union opposition due to opaque data governance), the "abandoned exoskeleton" case (poor workflow integration and training), and the "alert fatigue" case (high false-positive rates). These underscore the need for stakeholder engagement, user-centered design, and adaptive algorithms.

For sustained impact, WAD-derived leading indicators can be embedded within formal management systems like ISO 45001 (Clause 9.1/9.3) [50] and the PDCA cycle. This enables evidence-based planning, real-time feedback, and data-driven identification of systemic issues. Table 7 specifies decision pathways across operational, tactical, and strategic levels.

4.4 Positioning wearable assistive devices within the broader ecosystem of leading indicator technologies

WADs are one of several technologies for generating leading indicators. A mature safety system will likely integrate multiple data streams. Computer vision (CV) excels at population-level behavioral monitoring but cannot capture internal physiological states. Environmental IoT sensors quantify hazard presence but not human response. WADs uniquely capture dynamic human-state responses, providing the critical "human dimension".

A future-ready safety observability platform should pursue sensor fusion, integrating WAD-derived human-state data with CV-based behavioral analytics and IoT-derived environmental data. This enables risk triangulation, contextualized interpretation (e.g., fatigue due to heat + repetitive task), and personalized interventions. Table 8 provides a comparative analysis.

Table 7. Decision pathways for integrating wearable assistive devices (WADs)-derived data across organizational levels

Level	Data Input	Decision Output	Integration Point
Operational (real-time)	Individual WAD streams (e.g., hazardous posture detected)	Haptic feedback; supervisor notification for critical events	Edge processing layer; mobile alerts
Tactical (shift/weekly)	Aggregated exposure data (heat maps of postural stress by task/team)	Job rotation scheduling; task prioritization for ergonomic review	EHS (environment, health, and safety) dashboard; weekly safety meetings
Strategic (quarterly/annually)	Longitudinal trends (cumulative load distributions, adoption rates)	Capital planning for automation; training program redesign	Management review (ISO 45001); annual safety planning

Table 8. Comparative analysis of leading indicator technologies

Technology	Primary Strengths	Key Limitations	Complementarity with WADs
Computer vision (CV)	Non-intrusive, population-level monitoring, captures environmental context	Privacy concerns, limited to observable behaviors, cannot capture physiological states	CV provides external behavioral data; WADs provide internal physiological data
Environmental IoT sensors	Continuous exposure monitoring (air quality, noise, temperature), low-cost, scalable	No direct measurement of human response; cannot capture individual variability	IoT quantifies hazard presence; WADs quantify human exposure and response
AI-based fatigue detection (non-wearable)	Non-intrusive, leverages existing digital infrastructure	Limited to office/computer contexts; less validated for physical tasks	Useful for cognitive work; WADs essential for physically demanding roles
Wearable assistive devices (WADs)	Direct measurement of physiological, biomechanical, and cognitive states; real-time individual feedback; captures inter-individual variability	Adoption barriers (comfort, trust), maintenance, risk compensation, data governance challenges	WADs provide the human dimension missing from environmental and observational systems

Table 9. Practical recommendations for WADs implementation

Recommendations	Objective	Key Implementation Considerations	Expected Impact
Pilot with leading indicator focus	Generate evidence on risk precursors, not just injury rates	Select high-risk task; define measurable indicators (e.g., % time in hazardous posture); involve workers	Builds credibility; data-driven business case for rollout
Integrate data into EHS dashboard	Enable continuous risk monitoring	Ensure IT compatibility (APIs); train safety staff in data interpretation; establish alert protocols	Enables proactive interventions; enriches risk assessments
Position as "personalized safety coaches"	Maximize user acceptance	Co-design with end-users; communicate well-being benefits; prohibit punitive use of data	Reduces resistance; mitigates risk compensation; fosters safety culture
Develop "safety data analyst" competency	Build organizational capacity	Upskill safety personnel in data analytics, biomechanics, human factors	Bridges gap between data collection and actionable insights
Establish lifecycle management protocol	Ensure sustained effectiveness	Integrate cleaning, charging, updates, calibration into procedures	Maintains reliability; prevents new risks (failure, hygiene)

Note: WADs = wearable assistive devices; EHS = environment, health, and safety; APIs = application programming interfaces

4.5 Critical implementation factors: Navigating human and organizational dimensions

Technology alone is insufficient. Key human and organizational factors determine WAD effectiveness. Human-centered design is paramount; poor usability consistently leads to rejection or improper use [11, 20, 43]. Trust and transparency regarding data use are essential to avoid perceptions of surveillance and build acceptance [10, 27]. Behavioral adaptation, such as risk compensation (e.g., lifting heavier loads), must be actively managed through training and safety culture reinforcement [51]. Finally, organizational readiness, including management commitment, integration into procedures, and resources for maintenance and data management, is decisive for success [21, 27, 28, 52]. Table 9 translates these challenges into evidence-based recommendations.

4.6 Limitations and future research directions

This review has several limitations. First, the search was confined to three databases, potentially excluding relevant grey literature. Second, substantial methodological heterogeneity across studies – in contexts, devices, and outcome measures – precluded meta-analysis. Third, an outcome measurement imbalance exists: biomechanical parameters were frequently assessed objectively, while cognitive and behavioral precursors relied predominantly on subjective scales. Fourth, most studies were short-term (<6 months), limiting insights into long-term efficacy and organizational integration. Fifth, contextual generalizability is constrained by the preponderance of studies in Western Europe and North America, as well as predominantly male samples. Finally, publication bias toward positive findings may overstate effectiveness.

Risk compensation warrants deeper analysis. The phenomenon – workers increasing effort or risk-taking when perceiving enhanced protection – was reported in multiple studies [22, 23, 51, 53, 54]. From a systems perspective, this effect may arise when WADs are perceived as safety-enhancing devices rather than assistive tools, leading to a recalibration of perceived risk thresholds. As physical strain is reduced, workers may increase task intensity, such as lifting heavier loads, working faster, or adopting less cautious postures [22, 51].

This adaptive response creates a systemic paradox: while WADs reduce biomechanical load at Level 1, they may increase exposure intensity or duration at Level 2, thereby partially offsetting overall safety benefits.

Measurement approaches varied across studies. Some used EMG to detect increased muscle activation in non-targeted body regions [1-8, 17-19, 21, 22, 32, 35-51, 55, 56], suggesting redistribution of load; others used behavioral observation to document increased work pace or heavier load selection [22, 51]. Importantly, risk compensation appears to exist along a continuum, influenced by task characteristics, device design, and organizational incentives.

Mitigation strategies identified in successful implementations targeted these underlying mechanisms: (1) training programs emphasizing that WADs reduce but do not eliminate risk; (2) feedback systems designed to reinforce safe behavior rather than solely signaling hazards; and (3) organizational policies that decouple WAD use from productivity pressures [23, 35, 57]. Without such measures, the net safety benefit of WADs may be reduced due to behavioral adaptation.

Beyond methodological limitations, the evidence base also reveals important negative findings that help explain variability in outcomes. Schwerha et al. [20] reported that 23% of manufacturing workers discontinued exoskeleton use within two weeks, primarily due to thermal discomfort, indicating that usability constraints may override biomechanical benefits. Okpala and Nnaji [22] identified risks such as over-reliance and skill degradation, suggesting that prolonged assistance may reduce workers' situational awareness of hazardous postures.

Several short-term field studies [53] reported no statistically significant reduction in musculoskeletal discomfort despite measurable biomechanical improvements. This discrepancy likely reflects the multifactorial nature of discomfort, which is influenced not only by biomechanical load but also by psychological, organizational, and individual factors.

Similarly, the 24-week RCT by Jakobsen et al. [35] demonstrated a significant reduction in near-miss events (41%) without corresponding changes in LTIFR, highlighting the temporal and causal gap between leading and lagging indicators.

Overall, these findings highlight that biomechanical efficacy alone does not guarantee sustained use or injury reduction. Instead, WAD effectiveness is shaped by interacting physiological, behavioral, and organizational factors, consistent with the multi-level structure of the HIM-WAD model.

Future research must prioritize longitudinal, multi-center field studies with standardized outcome measures, objective cognitive assessments (e.g., EEG, Fnirs [24, 58-61]), and diverse worker populations [62]. Investigating mediation pathways and contextual moderators, as outlined in the HIM-WAD framework, is critical over simplistic "WAD → injury reduction" hypotheses.

4.7 Testable propositions for future research

To guide hypothesis-driven testing of the HIM-WAD framework, we propose three core propositions for multi-level empirical investigation:

Proposition 1 (Physiological-to-Behavioral Cascade). Sustained WAD use resulting in ≥20% reduction in muscle activity (EMG) during repetitive tasks will be associated with a ≥15% decrease in hazardous posture frequency over a work shift, measured by IMUs.

Proposition 2 (Behavioral-to-Operational Mediation). The relationship between WAD use and reduced near-miss rates (Level 3) is mediated by reductions in hazardous posture frequency (Level 2), controlling for organizational safety climate and task variability.

Proposition 3 (Temporal Moderation of Risk Compensation). Long-term WAD adoption (>12 months) will show attenuated risk compensation behaviors compared to short-term use (<3 months), attributable to progressive neuromuscular adaptation.

Note: These propositions operationalize key HIM-WAD pathways. Thresholds (e.g., 20% EMG reduction) are illustrative, based on Table 4, and require refinement through context-specific pilot studies and adequately powered longitudinal designs.

5. CONCLUSIONS

The synthesis of 176 studies indicates that WADs are associated with reductions in key physiological risk factors, including muscle fatigue, cumulative load, and hazardous postures, which are linked to errors, near-miss events, and work-related musculoskeletal disorders. Direct evidence linking WADs to reduced injury rates remains limited, reflecting the hierarchical nature of accident causation where individual improvements are mediated by organizational factors.

The HIM-WAD reconceptualizes WADs as dynamic safety barriers managing risk at source via real-time human-state modulation. WAD-generated leading indicators enable transition from reactive Safety-I to proactive Safety-II governance.

Effective implementation requires human-centered design, user acceptance, transparent data governance, and system integration. Future research needs longitudinal studies and harmonized metrics to realize WADs' transformative potential.

Supplementary materials are provided as separate files, including the full list of included studies, quality appraisal results, thematic synthesis framework, and the PRISMA 2020 checklist.

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