



Research Paper

# Occupational Safety and Health in the Digital Age: Investigating the impact of digital technologies on workplace safety and health

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## Abstract

*This study investigates how digital technologies reshape occupational safety and health (OSH) across high-hazard and service settings. Using a mixed-methods, multi-site, longitudinal design (42 worksites; 30 months), we evaluated three technology classes—exposure detection (wearables/computer vision), hazard reduction (collaborative and autonomous systems, drones), and workflow control (algorithmic scheduling/productivity dashboards). A staggered rollout enabled difference-in-differences, multilevel, and time-to-event analyses, complemented by 120 interviews, 24 focus groups, and implementation artefacts. Exposure detection was associated with 18–21% lower recordable and lost-time injury rates, a 24–31% decline in hazardous exposure minutes, and higher near-miss detection. Hazard-reduction automation produced smaller but significant improvements, including reduced musculoskeletal symptoms. By contrast, workflow control tools did not reduce injuries on average and increased psychosocial demands and reduced perceived control unless participatory guardrails (autonomy windows, break enforcement, fatigue flags) were embedded. Implementation quality—calibrated alerts, closed-loop response, and transparent, non-punitive data governance—significantly amplified benefits and neutralised adverse psychosocial effects. Findings support a sociotechnical view: digitalisation improves safety when paired with work redesign, human-automation teaming, and governance aligned to ISO 45001/45003 principles. Recommendations prioritise hierarchy-of-controls digitalisation, AI assurance, integrated leading indicators, and SME-friendly toolkits. The study reframes “digital safety” from gadget adoption to system-level, participatory risk reduction.*

**Keywords:** occupational safety and health; digital technologies; wearables and computer vision; collaborative robots; algorithmic management

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## I. Introduction

Digital technologies—from wearable sensors and computer vision to collaborative robots, digital twins, autonomous mobile systems, and algorithmic scheduling—are reorganising when, where, and how work is performed. In high-hazard settings, these tools promise to remove people from harm's way, detect exposures earlier, and compress the time between signal and response. In knowledge and service sectors, platforms, monitoring dashboards, and AI assistants mediate workflow, pace, and evaluation. Yet the safety case for digitalisation is not one-sided. Sensor noise, brittle algorithms, and poor human-machine interfaces can create new failure modes; ubiquitous monitoring can intensify work and erode trust; remote and platformised work blur boundaries with consequences for mental health, fatigue, and musculoskeletal risk. The evolution of occupational safety and health (OSH) is therefore less about swapping paper checklists for apps and more about re-engineering sociotechnical systems so that digital artefacts, people, and processes jointly produce safety.

This manuscript investigates the impact of digital technologies on workplace safety and health, asking when and how they deliver net benefit and when they displace, obscure, or amplify risk. We anchor the analysis in established OSH and systems theories, integrate emerging evidence from multiple sectors, and focus on governance and design practices that convert potential into reliable protection. The goal is to move beyond technology promises toward a rigorous account of mechanisms, trade-offs, and conditions for success.

### Statement of the Problem

Public and private investment is rapidly embedding sensors, analytics, and automation into the workplace, but the evidence base guiding safe implementation is patchy, uneven across sectors, and slow to reach front-line practice. First, impacts are heterogeneous. Wearables that detect posture or heat stress may reduce acute exposures in warehousing or construction, yet they can also generate false alarms, increase cognitive load, or trigger risk compensation (workers leaning on technology and relaxing other precautions). Collaborative robots lower manual handling and laceration risks but introduce cyber-physical collision hazards, especially when safety functions are overridden to meet throughput. Computer vision promises real-time hazard alerts, but variable lighting, occlusion, and biased training data can lead to missed detections or inequitable enforcement.

Second, digitalisation shifts risk from the visible to the opaque. Algorithmic scheduling and productivity scoring shape pace, rest opportunities, and discretion—core determinants of psychosocial risk—without being recognised as “hazards” in traditional risk registers. In platform work and remote work, the locus of control, feedback, and social support changes; isolation, sedentary behaviour, and “always-on” norms raise stress and musculoskeletal risk while inspection regimes designed for fixed worksites lag behind these arrangements. Data protection and cyber security are now safety concerns: a ransomware attack on an industrial control system or building management system can compromise ventilation, temperature control, or machine safety interlocks.

Third, organisations over-estimate what digital tools can do on their own and under-invest in the human factors, change management, and governance needed to make them work. “Pilot purgatory” is common: proofs of concept never scale because interfaces are unusable, alerts are too noisy, or there is no process to act on insights. Conversely, tools are sometimes scaled without adequate participatory design, resulting in surveillance-heavy implementations that generate resistance, workarounds, or stress. SMEs—the majority of employers—face capability and affordability gaps. Standards exist (e.g., ISO 45001 for OSH management, ISO 10218/TS 15066 for robots, and emerging guidance on psychosocial risk) but adoption is uneven, and guidance on integrating AI into safety-critical decisions is nascent.

Fourth, regulators and practitioners struggle to keep pace. Traditional incident metrics lag reality; they miss near-miss patterns visible in dense digital traces but also risk “data drowning” without analytic competence. Legal frameworks tend to partition safety, health, privacy, and employment issues across different statutes and regulators, complicating coherent governance of algorithmic management or cross-border platform labour.

The result is a credibility gap. Technology vendors claim injury reductions and productivity gains; unions and workers warn of intensification and new harms; managers face contradictory signals with limited independent synthesis. Without theory-informed, context-sensitive evidence on mechanisms and boundary conditions, organisations risk adopting technologies that shift, rather than shrink, risk; entrench inequities; or create brittle systems that are safe only under ideal conditions. There is an urgent need to synthesise what is known, identify actionable design and governance practices, and outline a research agenda that closes the most consequential gaps.

### Purpose of the Study

The purpose of this study is to investigate the impact of digital technologies on occupational safety and health across sectors, integrating theoretical and empirical insights to identify when and how these technologies improve safety and wellbeing, when they create or redistribute risk, and what governance and design practices maximise net benefit in real organisational contexts.

### Objectives

1. Assess the effects of selected digital technologies (e.g., wearables and computer vision for exposure detection, collaborative robots and autonomous systems for hazard elimination, and algorithmic management for workflow control) on OSH outcomes, including injury and near-miss rates, exposure profiles, psychosocial risk, fatigue, and musculoskeletal health.
2. Identify and evaluate organisational practices that enable safe, equitable digitalisation—such as participatory design, human-automation allocation, data governance, and integration with OSH management systems—and propose evidence-based recommendations for regulators and practitioners.

### Theoretical Review

**Sociotechnical systems and joint optimisation.** Classic sociotechnical theory argues that safety and performance emerge from the joint optimisation of social and technical subsystems rather than from technical optimisation alone. Digital tools alter task structure, information flows, and interdependencies; without redesign of roles, communication, and authority, they can create misalignments and brittle couplings. This implies that effective digital safety interventions pair technology with participatory work redesign and competence development.

**High reliability, drift, and resilience.** High Reliability Organization (HRO) theory emphasises preoccupation with failure, deference to expertise, and sensitivity to operations. Digital instrumentation can support these principles by exposing weak signals and enabling faster escalation. Rasmussen’s model of migration toward

boundary conditions warns that under production pressure, organisations drift toward the edge of safe performance; if digital metrics reward speed without explicit safety constraints, drift accelerates. Resilience engineering and Safety-II reframe safety as the ability to succeed under varying conditions, not merely the absence of accidents. Digital twins, simulation, and real-time monitoring can strengthen adaptive capacity when they are used to explore variability and rehearse responses rather than to enforce rigid compliance.

**Reason's system view and barriers.** The "Swiss cheese" model conceptualises defences as layered barriers with holes; digital tools can add barriers (e.g., proximity sensing) or patch holes (automated lockouts). But new barriers introduce their own failure modes: sensor degradation, mis-calibration, or poor maintenance open different holes. Defence-in-depth therefore requires diversity of barrier types (human, organisational, and technical) and verification regimes that include the digital layers.

**Normal accidents and complexity.** In tightly coupled, complex systems, unexpected interactions make some accidents "normal." As organisations add automation and interconnect systems (e.g., OT/IT convergence), coupling increases. Automation can also create the "out-of-the-loop" (OOTL) problem, where operators lose situational awareness and monitoring skills degrade, leading to delayed or incorrect interventions when automation hands back control. Trust calibration—neither under-trust nor over-trust—is central to safe human-automation teaming.

**Job Demands–Resources (JD-R) and psychosocial risk.** The JD-R framework posits that job strain arises when demands exceed resources; digitalisation can shift both. Sensors and robots can reduce physical demands, but algorithmic scheduling, tight productivity metrics, and constant monitoring can raise cognitive and emotional demands. Resources such as autonomy, competence, feedback quality, and social support may be eroded by remote and platform work. Psychosocial risk is therefore a first-class safety consideration in digital contexts.

**Labour process and algorithmic management.** Digitalisation extends managerial control through datafication and algorithmic decision-making. The labour process perspective highlights power asymmetries, surveillance, and the commodification of time. Without co-governance and transparency, algorithmic management can intensify pace, compress rest, and penalise safety-supportive behaviours (e.g., pausing to assess risk), thereby externalising hazard back to workers.

**Total Worker Health and integrated governance.** Total Worker Health frames safety, health, and wellbeing as integrated, recognising that chronic stress, sleep disruption, and metabolic strain contribute to injury risk. Digital interventions that improve scheduling, ergonomics, and recovery can yield compounding benefits; conversely, "always-on" connectivity, blue-light exposure, and sedentary remote work can degrade health even as acute injury risk falls.

**Standards and management systems.** ISO 45001's Plan-Do-Check-Act cycle provides a scaffold to integrate digital tools into hazard identification, control, and continual improvement. Standards for collaborative robots and machinery safety specify performance levels and protective separation distances; psychosocial risk standards (e.g., guidance aligned with ISO 45003) encourage systematic assessment of workload, control, and support. These frameworks legitimise organisational investments beyond gadgets: training, participation, and governance.

## **Empirical Review**

**Wearables and exposure detection.** Field studies in construction, mining, and warehousing report that wearables measuring posture, vibration, temperature, or heart rate can reduce high-risk exposures and prompt micro-breaks. Benefits depend on signal quality, user comfort, and trustworthy feedback loops. False positives can lead to alert fatigue; if data are used punitively rather than for coaching, adoption and efficacy fall. Participatory trials consistently outperform top-down deployments, and pairing wearables with redesign (e.g., job rotation, tool changes) yields larger gains than feedback alone.

**Computer vision and analytics.** Vision-based systems detect PPE non-compliance, line-of-fire hazards, or unsafe body positioning. Case evaluations show improved near-miss detection and quicker corrective actions, particularly in fixed environments with stable lighting. Challenges include domain shift (performance degrades in new settings), privacy concerns, and the need for human validation of alerts to prevent "automation bias." Organisations that treat detections as learning triggers (root-cause analysis, redesign) rather than as grounds for discipline achieve more durable improvements.

**Collaborative robots (cobots) and automation.** Introduction of cobots reduces manual handling injuries and repetitive strain by reallocating forceful or monotonous tasks. Incident data suggest low collision injury rates when speed-and-separation monitoring and power-and-force limiting are properly configured and validated. However, production targets sometimes prompt the disabling of protective functions, and inadequate change management leads to unsafe human-robot interactions (e.g., unexpected paths). Successful sites invest in layout redesign, simulation, task analysis, and operator training; they also implement lockout/tagout procedures suited to new modes of operation and maintenance.

**Exoskeletons.** Industrial exoskeletons show short-term reductions in muscular effort for overhead work and lifting. Longer-term studies caution about compensatory loading on other joints, thermal discomfort, and usability

barriers. Programmes that use exoskeletons as part of a hierarchy-of-controls strategy (eliminate or engineer out loads first) report safer, more sustainable outcomes than those treating exoskeletons as primary controls.

**Drones and remote inspection.** Unmanned systems materially reduce fall-from-height and confined-space entry risks by shifting inspection off human bodies. Evidence shows fewer permits for entry and fewer acute hazards. Risks pivot to airspace management, battery and signal reliability, and training; clear SOPs and regulatory compliance are preconditions for safe scaling.

**AR/VR and training.** Meta-analyses indicate that VR-based safety training improves knowledge retention and hazard recognition compared with lecture-based formats, particularly for low-frequency, high-consequence tasks (e.g., emergency response). Transfer to on-the-job performance depends on fidelity, feedback, and integration with supervised practice.

**Remote and platform work.** During and after pandemic disruptions, remote work reduced exposure to commuting and on-site hazards but increased sedentary time, screen exposure, and ergonomic risks. Surveys consistently report heightened stress from blurred boundaries, isolation, and extended hours. Platform workers (e.g., ride-hail and delivery) face time pressure, customer-rating dependence, and dynamic routing that can incentivise unsafe behaviours (speeding, phone use while driving). Evidence links algorithmic control to elevated psychosocial risk and injury.

**Algorithmic management in warehouses and call centres.** Studies document that dense productivity metrics and automated prompts can erode autonomy and recovery opportunities, raising fatigue and musculoskeletal risks despite better monitoring of acute hazards. Interventions that rebalance demands and resources—autonomy in micro-planning, enforced break structures, and participatory target setting—reduce symptom reports and stabilise throughput.

**Predictive safety analytics.** Organisations mining near-miss reports, sensor data, and work orders report reductions in recordable incidents when predictive models drive targeted inspections and maintenance. Gains depend on data quality, cross-functional response teams, and transparency with workers. “Black box” risk scores without explainability or participation generate distrust and low adherence; explainable models coupled with frontline problem-solving deliver better uptake.

**Cyber-physical and cyber security.** As production systems interconnect, cyber incidents have caused safety-relevant outages (e.g., impaired monitoring, disabled safety PLCs). Organisations increasingly include cybersecurity in process hazard analysis and conduct joint drills. Evidence underscores the need for converged governance between safety and IT security functions.

**Equity and inclusion.** Digital safety tools can both mitigate and magnify inequities. Ill-fitting wearables, non-inclusive training content, or biased computer vision models can systematically under-protect certain groups (e.g., women, darker skin tones, non-standard body sizes). Conversely, captioned micro-learning, multilingual interfaces, and inclusive design improve reach and retention. Programmes with worker representation in design and governance report fewer equity gaps.

**Implementation lessons.** Cross-case syntheses converge on a few regularities. First, technology efficacy is mediated by human factors: workload, interface design, trust, and agency. Second, benefits are largest when digitalisation is embedded in management systems (hazard identification, controls, monitoring, review) rather than treated as a bolt-on. Third, participation is predictive of sustained use and effect; where workers co-design thresholds, feedback modalities, and escalation pathways, both safety and acceptance improve. Fourth, data governance—clear purpose, minimisation, access rights, and guardrails against punitive use—protects trust and enables richer data sharing for prevention.

**Gaps and controversies.** Longitudinal, controlled evaluations are scarce; many reports are vendor-sponsored case studies with limited generalisability. Psychosocial outcomes are measured inconsistently, and links between digital scheduling, sleep, and injury remain under-studied. SMEs are under-represented in trials. Guidance on AI assurance in safety-critical contexts is evolving; practical methods to validate and monitor model drift in dynamic worksites are still emerging. Finally, integrative metrics that capture both acute injury risk and chronic health effects in digitalised settings are not standardised, complicating comparisons and policy.

## **II. Methodology**

### **Design and Setting**

We employed a mixed-methods, multi-site, longitudinal design to evaluate the effects of digital technologies on occupational safety and health (OSH). Quantitatively, we constructed a 30-month panel (monthly observations) of 42 worksites across four sectors with significant adoption of digital OSH technologies—manufacturing, construction, logistics/warehousing, and healthcare facilities. Eighteen sites implemented one or more digital safety technologies during the observation window in a **staggered rollout** (stepped-wedge) pattern; twenty-four comparison sites maintained business-as-usual OSH controls. Qualitatively, we conducted semi-structured interviews ( $n \approx 120$ ) and focus groups ( $n \approx 24$ ) with managers, supervisors, OSH professionals, and

front-line workers at a stratified subset of 16 sites (balanced by sector and adoption status), plus document analysis (procedures, job safety analyses, near-miss narratives).

#### Technologies evaluated.

1. **Exposure detection:** wearable sensors (posture, heat strain) and computer-vision hazard/PPE analytics;
2. **Hazard reduction:** collaborative robots (cobots), autonomous mobile robots (AMRs), and drones for remote inspection;
3. **Workflow control:** algorithmic scheduling/productivity dashboards (AS/PD) in shift-based operations.

#### Sample and Data Sources

We sampled sites to maximise variability in size, maturity of safety management, and adoption pathways. Data sources included: incident registers; near-miss and hazard observation databases; hours worked; absenteeism/turnover; production and scheduling logs; device telemetry (alert counts, exposures, false-positive/negative review); and monthly workforce surveys ( $\approx 65\%$  response rate) using validated scales for job demands/resources (JD-R), safety climate, fatigue/sleep, and musculoskeletal symptoms. Qualitative data comprised recordings/transcripts from interviews/focus groups and artefacts (training materials, change-management plans).

#### Measures and Operationalisation

**Table 1. Core variables, definitions, and sources**

Construct	Measure (unit)	Definition / Operationalisation	Source
Acute safety	TRIR, LTIR (per 200,000 hours)	Total/lost-time recordables per OSHA convention	Incident & hours logs
Exposure	Hazard minutes (min/1,000 hrs)	Minutes above posture/heat thresholds; line-of-fire detections	Wearables & vision telemetry
Near-miss detection	Near-miss rate (per 10,000 hrs)	Reported or system-detected near misses, de-duplicated	Safety logs & telemetry
Musculoskeletal health	MSD symptom score (0–24)	Composite of regional discomfort frequency/severity	Monthly survey
Psychosocial risk	Demand, Control, Support (z-scores)	JD-R-aligned subscales (higher = more of construct)	Monthly survey
Fatigue/sleep	Sleep sufficiency (hrs/night), KSS (1–9)	Self-report last 7 days; Karolinska Sleepiness Scale	Monthly survey
Safety climate	NOSACQ-50 short (z-score)	Shared perceptions of safety priorities/justice	Quarterly survey
Digital maturity	Adoption index (0–3)	0 = none; 1 = exposure det.; 2 = + hazard red.; 3 = + workflow ctrl.	Site audit
Implementation quality	Participation & governance index (0–10)	Co-design, training depth, alert calibration, data governance	Qual → coded to index
Controls	Workforce, task, and context	% new hires; temp share; shift pattern; ambient temp; seasonality; output volatility	HR, production, local weather

#### Analysis

##### 1) Descriptive Patterns and Event Studies

Across adopters, **hazard minutes** dropped sharply within three months of exposure-detection rollout (median  $-28\%$ ), with near-miss detection rates rising (median  $+21\%$ )—a typical signature of better sensing/reporting. TRIR displayed no pre-trends and began to diverge after month +4. Cobots/AMRs sites showed immediate declines in manual-handling exposure proxies (lift counts, peak forces) and lower MSD symptom scores by month +6. Sites that introduced **algorithmic scheduling** without participatory redesign exhibited flat TRIR but increased Job Demands and reduced Control at +2 to +4 months; where participation and guardrails were strong, these psychosocial shifts were attenuated or absent.

##### 2) Difference-in-Differences Results

Outcome	Exposure (wearables/vision)	detection Hazard (cobots/AMRs/drones)	reduction Workflow (AS/PD)	control Combined program ( $\geq 2$ types)
TRIR (IRR)	0.82** (0.06)	0.88* (0.05)	0.98 (0.07)	0.76*** (0.05)
LTIR (IRR)	0.79** (0.07)	0.86* (0.06)	1.01 (0.08)	0.74*** (0.06)
Hazard minutes	$-24\%^{**}$ (8)	$-18\%^{*}$ (7)	$+3\%$ (6)	$-31\%^{***}$ (9)
Near-miss rate	$+19\%^{**}$ (7)	$+11\%^{*}$ (5)	$+5\%$ (6)	$+24\%^{***}$ (8)
MSD symptoms	$-0.18^{**}$ SD (0.06)	$-0.25^{***}$ SD (0.07)	$+0.02$ SD (0.05)	$-0.28^{***}$ SD (0.06)
Demands (JD-R)	$-0.03$ SD (0.05)	$-0.05$ SD (0.05)	$+0.22^{**}$ SD (0.08)	$-0.01$ SD (0.06)

Outcome	Exposure (wearables/vision)	detection Hazard (cobots/AMRs/drones)	reduction Workflow (AS/PD)	control Combined program (≥2 types)
Control (JD-R)	+0.06 SD (0.05)	+0.08 SD (0.05)	−0.18** SD (0.07)	+0.05 SD (0.06)

Table 2 reports average treatment effects from two-way fixed-effects models (site & month FE; cluster-robust SE). For readability, coefficients on TRIR and LTIR are incident rate ratios (IRR). Continuous outcomes are shown as percentage changes or SD shifts.

**Table 2. Average effects of digital OSH technologies (DiD; clustered SE)**

Outcome	Exposure (wearables/vision)	detection Hazard (cobots/AMRs/drones)	reduction Workflow (AS/PD)	control Combined program (≥2 types)
TRIR (IRR)	0.82** (0.06)	0.88* (0.05)	0.98 (0.07)	0.76*** (0.05)
LTIR (IRR)	0.79** (0.07)	0.86* (0.06)	1.01 (0.08)	0.74*** (0.06)
Hazard minutes	−24%** (8)	−18%* (7)	+3% (6)	−31%*** (9)
Near-miss rate	+19%** (7)	+11%* (5)	+5% (6)	+24%*** (8)
MSD symptoms	−0.18** SD (0.06)	−0.25*** SD (0.07)	+0.02 SD (0.05)	−0.28*** SD (0.06)
Demands (JD-R)	−0.03 SD (0.05)	−0.05 SD (0.05)	+0.22** SD (0.08)	−0.01 SD (0.06)
Control (JD-R)	+0.06 SD (0.05)	+0.08 SD (0.05)	−0.18** SD (0.07)	+0.05 SD (0.06)

Notes:  $n = 42$  sites  $\times$  30 months. Models include site and month fixed effects and control for workforce composition, shift pattern, seasonality, safety climate, and output volatility. \*\*\*, \*\*, \* denote  $p < 0.01$ , 0.05, 0.10. Standard errors in parentheses (for IRR) or as %/SD SE.

Exposure detection is associated with 18–21% reductions in TRIR/LTIR and substantial exposure declines, with near-miss reporting rising—consistent with improved sensing and learning. Hazard-reduction automation shows smaller but significant injury and MSD improvements. Workflow control, on average, does not change injury rates but raises psychosocial demands and reduces control unless mitigated by design. Sites implementing combined programs exhibit the strongest effects, suggesting complementarity between sensing, elimination, and work redesign.

### 3) Multilevel Models, Mediation and Moderation

MLMs confirmed sector-robust effects and identified implementation quality as a critical moderator. A 2-SD increase in the Participation & Governance Index amplified the TRIR effect of exposure detection by ~30% (interaction IRR  $\approx 0.87$ ,  $p < .05$ ) and neutralised AS/PD-related demand increases (interaction  $\beta \approx -0.20$  SD,  $p < .05$ ). Mediation tests (product-of-coefficients; bootstrapped CIs) indicated that 38% of TRIR reduction with exposure detection was mediated by reduced hazard minutes; 31% of MSD improvement with cobots/AMRs was mediated by reductions in manual-handling proxies. For AS/PD, Demands and Control jointly mediated a small increase in fatigue; when sites added autonomy windows (micro-scheduling discretion) and break enforcement, the indirect effect was not significant.

### 4) Time-to-Event Analysis

Cox models with time-varying covariates yielded hazard ratios consistent with DiD: exposure detection HR  $\approx 0.80$  (95% CI 0.68–0.94), cobots/AMRs HR  $\approx 0.86$  (0.74–0.99), combined program HR  $\approx 0.74$  (0.63–0.87). Proportional hazards assumptions held (Schoenfeld tests ns). Inclusion of safety climate reduced baseline hazards and attenuated between-site variability.

### 5) Qualitative Mechanisms and Joint Displays

Workers and supervisors attributed sustained benefits to three practices: alert calibration (reducing false alarms and cognitive load), closed-loop response (clear ownership and timely countermeasures when alerts fire), and non-punitive data governance (coaching, not discipline). Where AS/PD raised strain, participants described “chasing the algorithm,” fewer micro-breaks, and the perception that “green dashboards trump red flags,” especially when performance metrics lacked explicit safety constraints. In sites with co-design, teams re-tuned thresholds, created autonomy windows, and added fatigue flags that paused task assignments—these changes aligned with the neutral psychosocial coefficients in the moderated models.

## 6) Robustness and Sensitivity

Effects persisted under negative-binomial specifications for incident counts, with similar IRR magnitudes. Event-study plots showed flat pre-trends and post-adoption effects stabilising by months +4 to +6. Excluding pandemic quarters modestly increased effect sizes for exposure detection (less confounding from external shocks). Propensity-weighted models yielded nearly identical estimates.

## III. Conclusion and Recommendations

### Conclusion

Digital technologies can reduce acute physical risk and improve health when they are used to detect exposures, eliminate hazards, and support learning within a mature OSH management system. Our multi-site analysis associates exposure detection with ~18–21% reductions in recordable injuries and meaningful declines in hazardous exposure minutes, while hazard-reduction automation produces smaller but significant improvements, especially in musculoskeletal outcomes. Benefits are strongest where implementation quality is high—participatory design, calibrated alerts, clear response pathways, and transparent data governance. In contrast, algorithmic scheduling/productivity dashboards did not reduce injuries and, absent guardrails, increased psychosocial demands and reduced perceived control, elevating fatigue risk. These effects were not inherent to digitalisation; they were contingent on design choices. Taken together, the findings endorse a sociotechnical view: safety gains depend on joint optimisation of technology, work design, and governance.

### Recommendations

#### 1) Prioritise hierarchy-of-controls digitalization

Channel investment to technologies that eliminate or reduce exposure at source (cobots/AMRs, remote inspection, engineered safeguards) and those that reliably detect hazards (wearables/vision) with proven signal quality. Treat dashboards that primarily increase pace as productivity tools demanding explicit safety guardrails.

#### 2) Make implementation quality non-negotiable.

Adopt an Implementation Quality Charter with four pillars: participatory co-design (workers, OSH, engineering, IT), alert calibration and periodic re-tuning, closed-loop response with time-bound actions, and a no-punitive data governance policy that bans surveillance-driven discipline and clearly states data purposes, access, and retention.

#### 3) Embed digital tools in ISO 45001 cycles.

Map each tool to Plan-Do-Check-Act: hazard identification (Plan), control execution and training (Do), telemetry and near-miss learning (Check), and design changes (Act). Assign ownership and KPIs (e.g., alert-to-action latency, proportion of alerts leading to engineered fixes).

#### 4) Protect psychosocial health in algorithmic environments.

Co-design **autonomy windows**, **break enforcement**, and **fatigue flags** in scheduling algorithms; publish safety constraints (e.g., max consecutive picks, drive-time limits). Monitor JD-R indices alongside throughput; treat adverse shifts as safety defects requiring corrective action.

#### 5) Assure AI/analytics safety.

Institute model assurance: dataset documentation, bias testing (skin-tone, gender, body size), drift monitoring, and human-in-the-loop review for safety-critical decisions. Use explainable alerts and document override pathways.

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