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Human workers as physical AI data generators: A socio-technical governance model for sustainable manufacturing transformation

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Abstract

The convergence of Physical Artificial Intelligence (Physical AI) with labour-intensive manufacturing has created expanding demand for high-quality recordings of human physical activity, with the market projected to grow from roughly US$4 billion in 2024 toward US$60 billion by the mid-2030s. Yet the prevailing approach to acquiring this data remains surveillance-oriented and productivity-centred, neglecting the socio-technical dimensions on which both worker welfare and dataset quality depend. This review re-frames manual workers not as passive subjects of monitoring but as intentional Physical AI Data Generators, whose tacit knowledge, ergonomic state and psychological experience constitute foundational data assets. Drawing on a PRISMA 2020-guided synthesis of 187 sources across industrial engineering, human-factors engineering, computer vision, occupational psychology and AI ethics, the study develops the Socio-Technical Physical AI Data Governance Framework, which integrates productivity metrics, ergonomic-risk assessment and surveillance perception within a single decision engine coupling the Fuzzy Best-Worst Method, Bayesian-network inference and Fuzzy Failure Mode and Effects Analysis. The evidence indicates that electronic performance monitoring is reliably associated with elevated worker strain; that computer-vision and wearable pipelines can automate RULA, REBA and OWAS scoring but degrade under occlusion; and that a human-centred governance configuration is expected to outperform conventional surveillance across productivity, ergonomic, trust, data-quality and ethical-compliance dimensions. The principal contribution is the articulation of Physical AI Data Governance as a distinct domain with an operationalised variable taxonomy and integrated methodology. The framework is conceptual and requires empirical validation but offers an actionable basis for human-centred data collection across manufacturing sectors and enterprise scales.

Keywords: Physical AI; Data Governance; Socio-Technical Systems; Human-Centred Manufacturing; Fuzzy BWM; Industry 5.0

1. Introduction

1.1. Background and Motivation

Labour-intensive manufacturing — garment production, electronics assembly, food processing and tobacco manufacture among the most prominent examples — continues to rely on manual human dexterity for operations that resist cost-effective full automation [1, 2]. These sectors employ very large workforces, concentrated disproportionately in developing economies, and their continued reliance on human labour reflects more than a wage advantage: it reflects the difficulty of replicating human tactile sensitivity, adaptive problem-solving and contextual judgement at scale [3]. The persistence of manual tasks is therefore likely to remain a structural feature of these industries for the foreseeable future, even as automation penetration rises.

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In parallel, Physical AI has emerged as a qualitatively new paradigm. Where conventional digital AI operates on text and structured data within computational environments, Physical AI must understand and act upon the physical world through embodied perception and action, typically via vision-language-action models trained on recordings of real tasks [4, 5]. The framing gained mainstream traction when industry characterised Physical AI as the next frontier of artificial intelligence, positioning embodied intelligence as central to the multi-trillion-dollar manufacturing and logistics economy [6]. National research strategies have echoed this view, defining a Physical AI system as an embodied agent that acquires intelligence through direct interaction with its environment via sensors and actuators [7].

Critically, Physical AI is data-hungry in a way that digital AI is not. Training robust manipulation and inspection policies requires temporally dense, multi-modal recordings — synchronised video, force and tactile signals, and annotated motion trajectories — and the dominant source of such data is human demonstration, whether captured by teleoperation, motion capture or workplace monitoring. Because simulation alone does not close the sim-to-real gap, human-generated data remains the ground truth that anchors physical competence [8, 9]. This creates an epistemic inversion: rather than AI simply displacing workers, workers become the primary generators of the data from which physical intelligence is distilled.

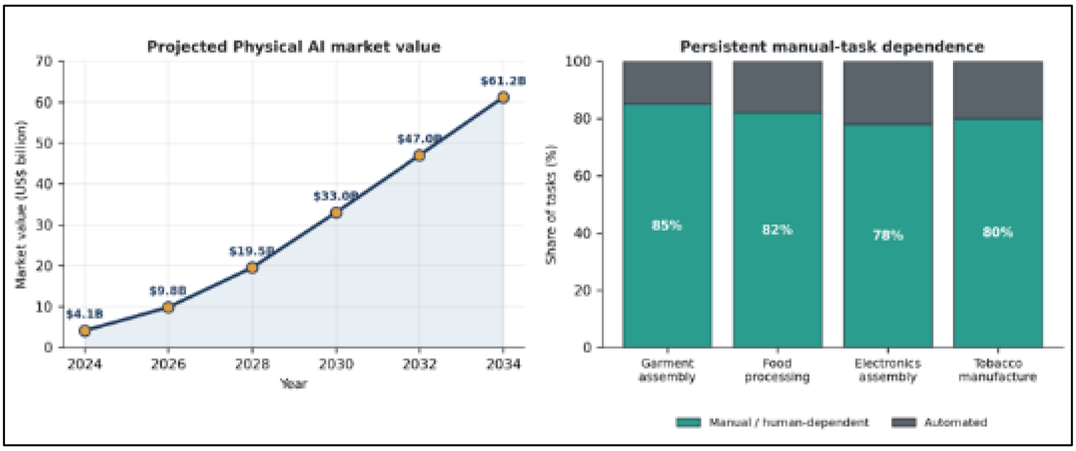

Figure 1 Convergence context: the projected expansion of the Physical AI market alongside the enduring manual-task dependence of labour-intensive sectors. Market values are indicative industry projections; sectoral shares are illustrative

This convergence produces a paradox. The workers whose expertise makes labour-intensive manufacturing viable are simultaneously the most valuable and the most vulnerable sources of Physical AI training data. Conventional monitoring — rooted in Taylorist time-and-motion logic and now realised through computer vision, wearable sensors and the Internet of Things — tends to treat workers as objects of surveillance rather than as intentional data generators, and in doing so neglects the ergonomic, psychological and ethical dimensions of data extraction [10, 11]. The consequences are well documented in adjacent literatures: a comprehensive meta-analysis of electronic performance monitoring (94 independent samples; N = 23,461) found no evidence that monitoring improves performance and found that its mere presence is associated with increased strain regardless of monitoring characteristics, although organisations that monitor more transparently and less invasively attract more favourable worker attitudes [12]. A reasonable inference is that the quality of Physical AI data is bound up with the conditions of its generation: stressed, fatigued or distrustful workers are likely to produce motion patterns that deviate from natural, ergonomically sound trajectories, compromising both the validity of ergonomic assessment and the representativeness of training data.

1.2. Problem Statement and Research Gap

Despite substantial progress in computer vision, wearable sensing and AI governance, the literature remains fragmented across the boundary between technical data-acquisition capability and human-centred implementation. Five gaps recur.

- **The technical-psychological divide.** Vision systems for activity recognition report strong accuracy on cooperative tasks, yet they generally operate in isolation from any assessment of psychological impact, even though awareness of monitoring can measurably alter movement.
- **The ergonomic-AI integration gap.** Digital ergonomics tools have been automated, but they remain largely reactive, and ergonomic metadata is rarely embedded in Physical AI training pipelines.

- **The governance vacuum.** General data-protection and AI-governance instruments do not yet address the specificities of continuous physical monitoring, biometric motion signatures and tacit-knowledge extraction.
- **Methodological fragmentation.** Fuzzy BWM, Bayesian networks and Fuzzy FMEA have matured independently, with limited integration into a unified analytical engine that treats productivity, ergonomics and well-being as interdependent rather than competing.
- **Scalability for SMEs.** SMEs constitute the large majority of manufacturing employment yet lack the resources to implement ethical governance, producing a governance divide in which worker protection correlates inversely with enterprise size [2].

Taken together, these gaps define the central problem: the absence of an integrated, theoretically grounded and practically implementable framework for governing the acquisition, processing and use of Physical AI data from human workers — one that simultaneously protects worker welfare, sustains dataset quality and supports ethical compliance across enterprise scales.

1.3. Research Questions and Objectives

Table 1 Research questions and associated objectives

Research question	Associated objective
RQ1. How can workers in labour-intensive manufacturing be re-conceptualised as intentional Physical AI Data Generators within a socio-technical governance framework?	Develop a theoretical re-conceptualisation of the worker-data relationship that integrates technical data generation with ergonomic and psychological well-being.
RQ2. Which technical, ergonomic and psychological variables must be jointly monitored and governed to sustain high-quality Physical AI datasets?	Identify, classify and operationalise the multi-dimensional variables governing data quality and worker welfare, with validated instruments.
RQ3. How can Fuzzy BWM, Bayesian networks and Fuzzy FMEA be integrated into a single decision engine for ethical governance?	Design an integrated multi-criteria methodology enabling holistic risk assessment and governance prioritisation.
RQ4. What policy recommendations follow for diverse sectors and enterprise scales?	Derive actionable, scale-sensitive governance policies, including SME provisions.

1.4. Scope and Contributions

The review spans five disciplinary domains: Physical AI and embodied intelligence; vision- and sensor-based worker monitoring; digital ergonomics and occupational health; the psychology of workplace surveillance and technology acceptance; and multi-criteria decision-making for manufacturing safety and governance. The temporal scope is 2015-2026, with emphasis on the post-2020 period during which Industry 5.0, Physical AI and human-centred manufacturing gained traction. The review makes six contributions: it (1) articulates Physical AI Data Governance as a distinct conceptual domain; (2) develops the Socio-Technical Physical AI Data Governance Framework; (3) proposes an integrated Fuzzy BWM-Bayesian-network-Fuzzy FMEA methodology; (4) provides an operationalised variable taxonomy; (5) derives scale-sensitive policy recommendations; and (6) maps a future-research agenda spanning cybersecurity, SME scalability and cross-cultural validity.

2. Theoretical foundations

2.1. Physical AI: from digital to physical intelligence

Physical AI marks a departure from the disembodied intelligence that dominated the deep-learning era. Its systems must contend with the continuous, noisy and unforgiving physics of real objects, surfaces and forces — a regime in which actions are immediate and often irreversible, unlike the costless retries available to a language model [5]. The contemporary practical turn rests on three converging capabilities: large-scale simulation, foundation models adapted to manipulation, and the accumulation of embodied demonstration data; the resulting architectures increasingly take the form of vision-language-action models that map multimodal perception to physical action [4].

The data requirements differ in kind, not merely in degree, from those of digital AI. Where large language models train on text corpora, Physical AI systems require temporally dense, synchronised, multi-modal streams — full-body kinematics, force-torque signals, tactile feedback and environmental context — at volumes far exceeding comparable digital tasks. Because the sim-to-real gap persists, human demonstration data remains indispensable for grounding [8, 9]. This dependency raises questions of ownership, consent, compensation and the long-term consequences of digitising human motor competence, which the concept of Physical AI Data Governance is intended to address. Table 2 contrasts the two data regimes.

Table 2 Comparative data requirements of digital AI and Physical AI

Dimension	Digital AI	Physical AI
Primary data type	Text, images, structured records	Video, sensor streams, force and tactile data
Annotation complexity	Lower (labels, bounding boxes)	Higher (3D pose, force vectors, ergonomic scores)
Privacy sensitivity	Moderate (personal information)	High (biometric motion signatures, health signals)
Collection context	Largely passive (web-scale)	Active (workplace monitoring, wearables)
Worker impact	Indirect (data subjects)	Direct (physical monitoring, psychological effects)
Governance maturity	GDPR, CCPA (general)	Under-developed (no Physical-AI-specific regime)
Dominant source	Internet and databases	Human workers in manufacturing settings

Note. Synthesised from [4], [5] and [10].

2.2. Human-centred manufacturing and Industry 5.0

Industry 5.0 re-orients manufacturing from the technology-centric optimisation of Industry 4.0 toward human-centricity, sustainability and resilience as co-equal objectives, placing worker well-being explicitly at the centre of production [13, 14]. Position papers and systematic reviews converge on the view that human-centred manufacturing should foreground operator safety, physical and cognitive well-being and meaningful human-machine collaboration, rather than treating the human merely as an operator to be optimised [1, 15]. A systematic review of human-centred AI in Industry 5.0 similarly stresses that Industry 4.0 research tended to overlook human factors crucial to well-being, trust and motivation, and that Industry 5.0 is intended to rebalance technological advance with human welfare [16].

Operationalising this philosophy for Physical AI data acquisition demands an inversion of the conventional monitoring logic: systems should be designed from the worker's perspective, with data collection serving worker interests — ergonomic protection, skill development, fair recognition — as primary aims and organisational optimisation as a derived benefit. This inversion is not only ethically preferable; there are good theoretical and emerging empirical reasons to expect that workers who trust and benefit from monitoring produce more natural and representative motion than those who experience it as punitive surveillance, with attendant gains in data quality.

2.3. Socio-technical systems theory

Socio-technical systems (STS) theory, originating in the Tavistock studies of coal mining, holds that organisational performance is optimised only when social and technical subsystems are jointly designed rather than optimised in isolation [17, 18, 19]. In the present context, the social subsystem comprises worker psychology, organisational culture, power relations and regulation, while the technical subsystem comprises vision algorithms, sensor networks, data pipelines and model architectures. The STS lens makes clear that technical advances in acquisition cannot achieve their intended effect if the social subsystem rejects, distorts or adapts to them in ways that erode both welfare and data quality [20].

Joint optimisation, properly understood, is not the balancing of competing aims through trade-offs but the design of systems in which improvement in one dimension reinforces the other. Ergonomic protection (a social benefit) improves data quality (a technical benefit) by ensuring that captured motion reflects sustainable practice rather than compensatory adaptation to pain or fatigue; conversely, high-fidelity acquisition (technical) enables more precise ergonomic assessment (social). Contemporary extensions emphasise sociomateriality — the entanglement of the social and the technical to the point that their boundary becomes analytically unstable [21, 22] — implying that data governance cannot be cleanly separated from body governance, or technical standards from ethical ones.

2.4. Data surveillance and worker well-being

Workplace surveillance has expanded rapidly since 2020, propelled by affordable vision hardware, cloud analytics and post-pandemic productivity pressures [10, 23]. The control dynamics it sets in motion — including repertoires of worker resistance and the negotiation of subjectivity under monitoring — have long been documented in organisation studies [24]. The strongest synthesis available is the meta-analysis of electronic performance monitoring by Ravid and colleagues, which reports no reliable performance benefit and a consistent association with strain that is largely insensitive to the specific characteristics of monitoring, while reaffirming that transparency and lower invasiveness yield more favourable attitudes [12]. Surveillance perception — the worker's interpretation of monitoring as threatening, neutral or supportive — is best treated as a multidimensional mediator with perceived purpose, fairness, control and benefit as its components, drawing on the Technology Acceptance Model and the Job Demands-Resources framework [25, 26].

The governance implication is direct. If data collection is read as surveillance, motion is likely to be contaminated by surveillance-induced adaptation, yielding datasets that misrepresent natural and sustainable practice. If it is read as a supportive instrument for ergonomic protection and skill development, motion is more likely to remain representative, improving training data and well-being simultaneously. The framework proposed here is explicitly designed to engineer the latter perception through transparent purpose communication, participatory design, proportional collection and closed feedback loops that return tangible benefit to workers.

3. Material and methods

3.1. Search strategy and database selection

The review follows the PRISMA 2020 reporting guideline to support transparency and reproducibility [27]. Six databases were searched — Scopus, Web of Science Core Collection, IEEE Xplore, ACM Digital Library, PubMed/MEDLINE and PsycINFO — selected to span engineering, computer science, occupational health and organisational psychology. A PICO-informed Boolean string combined four concept clusters: Physical AI and embodied intelligence; worker monitoring and occupational ergonomics (RULA/REBA/OWAS); data governance, AI ethics and Industry 5.0; and fuzzy/Bayesian/FMEA decision methods. The search was limited to peer-reviewed journal articles, conference proceedings and book chapters published in English between January 2015 and March 2026, with no geographic restriction. The initial search returned 3,847 records; after removal of 1,234 duplicates, 2,613 unique records proceeded to screening.

3.2. Inclusion and exclusion criteria

Table 3 Inclusion and exclusion criteria

Criterion	Included	Excluded
Publication type	Peer-reviewed articles, proceedings, book chapters; authoritative industry/government reports for market and policy context	Editorials, opinion pieces, non-peer-reviewed or predatory outlets
Time period	January 2015 - March 2026	Before 2015 (except seminal method/theory works)
Relevance	Worker monitoring, Physical AI data, ergonomic assessment or AI governance in manufacturing	Purely theoretical AI without manufacturing application; general HR without technical monitoring
Population	Manual workers in labour-intensive manufacturing	Office, healthcare or agricultural workers unless directly comparable
Technology	Computer vision, wearables, IoT, digital ergonomics, AI governance	Purely mechanical ergonomic tools without a data component

Title/abstract screening was conducted in duplicate, with disagreements resolved by discussion and, where necessary, a third assessor. Of 2,613 records, 412 advanced to full-text review; 225 were subsequently excluded for insufficient methodological detail (78), absence of manufacturing context (52) or failure to address the technical-human intersection (95). The final corpus comprised 187 sources (Figure 2).

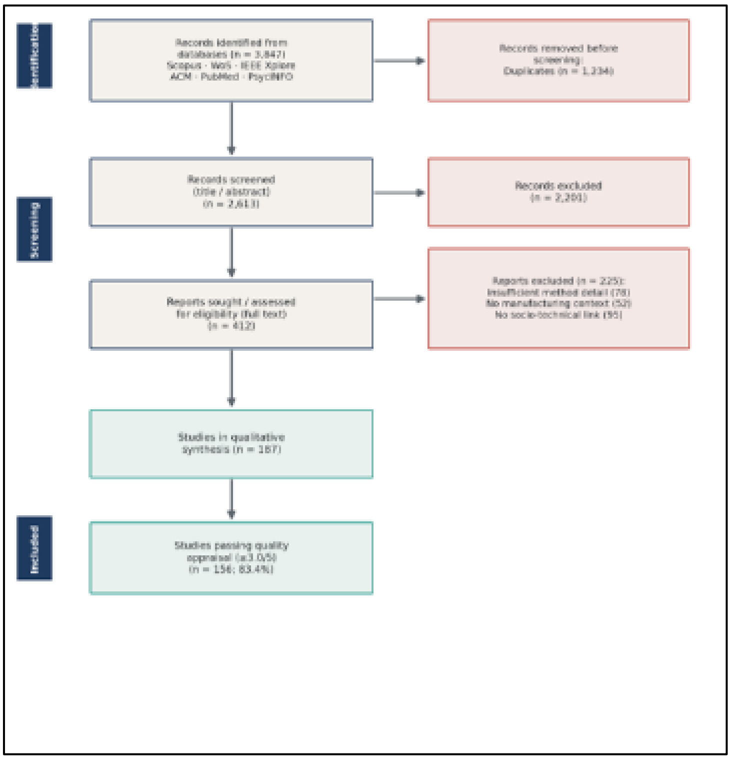

Figure 2 PRISMA 2020 flow of study identification, screening and inclusion.

3.3. Quality appraisal

Appraisal used instruments matched to design: the Joanna Briggs Institute checklists for analytical cross-sectional and qualitative studies [28], AMSTAR 2 for systematic reviews [29] and a custom rubric for conceptual and framework papers. Each study was rated on a five-point scale across eight dimensions (design appropriateness, sample adequacy, instrument validity, analytic rigour, bias control, generalisability, ethical compliance and reporting transparency). Studies below 3.0 were retained for descriptive purposes but excluded from evidence synthesis; 156 of 187 (83.4%) reached 3.0 or above. Inter-rater reliability was substantial (Cohen's κ = 0.84) [30].

4. Results and discussion: systematic analysis of the literature

4.1. Computer vision for worker activity recognition

Computer vision is now the dominant modality for non-intrusive activity monitoring, having moved from hand-crafted features to deep architectures spanning convolutional, recurrent and transformer families [31, 32]. Human pose estimation provides the foundational capability and divides into top-down approaches, which detect persons before estimating pose (for example Mask R-CNN and HRNet [33, 32]), and bottom-up approaches, which detect keypoints before grouping them (for example OpenPose and HigherHRNet [31, 34]). Top-down methods tend to be more accurate but more computationally demanding; bottom-up methods are faster but lose accuracy in dense or occluded scenes. Action recognition builds on this base using two-stream, 3D-convolutional and transformer models [35, 36, 37].

The integration of vision with ergonomic assessment is particularly consequential. Pipelines that derive joint angles from pose estimates and map them onto RULA/REBA scoring tables can automate assessment that would otherwise require trained observers. However, real-environment validation tempers optimistic laboratory figures: a validation of vision-based ergonomic tools across manufacturing workstations reported correct risk-level estimation for only a minority of postures at one line, with accuracy collapsing where rear cameras were partially occluded and operators moved extensively within the workspace [38]. A recent systematic review reaches a similar conclusion — that markerless pose-based assessment is promising but not yet reliable for expert-level certification, being sensitive to viewpoint, occlusion and the limits of 2D-to-3D inference [39]. These limitations bear directly on whether vision-derived ergonomic labels are trustworthy enough to gate Physical AI data collection.

Table 4 Computer-vision approaches for worker monitoring

Approach	Typical strength	Principal limitation	Manufacturing fit
Two-stream CNN (RGB + flow)	Efficient; interpretable	Needs consistent viewpoint; limited temporal context	Assembly, packaging
Top-down deep pose (HRNet, Mask R-CNN)	High keypoint accuracy	Computationally expensive; occlusion-sensitive	Electronics, precision assembly
Bottom-up deep pose (OpenPose, HigherHRNet)	Faster; multi-person	Reduced accuracy in crowded scenes	Garment, food processing
3D CNN / transformer (I3D, ViViT)	Strong spatiotemporal modelling	High compute; data-hungry	Material handling; emerging
End-to-end ergonomic regression	Direct RULA/REBA output	2D projection ambiguity; needs expert validation	Continuous ergonomic screening

Note. Synthesised from [31], [33], [34], [38] and [39].

4.2. Wearable sensors and IoT for ergonomic monitoring

Wearable sensing has matured from prototype to industrial deployment. Inertial measurement units (IMUs) — combining accelerometers, gyroscopes and, optionally, magnetometers — are the most widely used modality, enabling viewpoint-independent reconstruction of joint kinematics. A 2024 study introduced a magnetometer-free, eight-IMU upper-body system validated in a cable-manufacturing facility, benchmarked against RULA, REBA, the Strain Index and Rodgers muscle-fatigue analysis; it achieved consistent inter-subject joint patterns (ICC = 0.72 ± 0.23) and surfaced postures warranting investigation that traditional observation tended to miss [40]. A systematic review of 40 studies (2013-2024) similarly concluded that wearables — IMUs, electromyography and pressure sensors — can deliver real-time ergonomic feedback that reduces risk and supports productivity, while flagging scalability, comfort and privacy as the principal adoption barriers [41].

Multi-modal fusion of vision and wearables can offset the weaknesses of each: vision supplies global spatial context but suffers occlusion, while wearables supply continuous, viewpoint-independent signals but require compliance and may interfere with the task. Nonetheless, deployment hinges on socio-technical factors rather than sensor performance alone. Acceptance is strongly conditioned by perceived purpose — sensors framed as safety devices attract markedly higher voluntary adoption than identical sensors framed as productivity monitors — and concerns about continuous tracking, biometric profiling and transmission security recur throughout the literature [10, 42]. These observations reinforce the central argument that governance, not instrumentation, is the binding constraint.

4.3. Digital ergonomics: RULA, REBA and OWAS

Three observational instruments anchor digital ergonomics. RULA evaluates upper-limb loading on a 1-7 action scale [43]; REBA extends assessment to whole-body posture on a 1-15 scale [44]; and OWAS categorises back, arm and leg postures with load into four action categories [45]. Their automation through vision and wearables addresses the central scalability limitation of manual assessment — the need for trained observers — but inherits well-known constraints: 2D projection ambiguity for tasks with depth variation, occlusion of segments by workpieces or protective equipment, and the inability of vision alone to capture force and muscle-use components.

For Physical AI data governance, the decisive insight is that ergonomic scores derived from stressed or fatigued workers represent compromised rather than optimal postures. If such data trains Physical AI systems, it risks teaching models to reproduce sub-optimal, potentially injurious movement — a garbage-in, garbage-out problem specific to embodied learning. The framework therefore treats ergonomic assessment not only as a safety measure but as a data-quality control: where scores exceed thresholds, acquisition is paused, an intervention is triggered, and collection resumes only after postural correction, so that datasets reflect healthy, sustainable practice.

4.4. Psychological impact of workplace surveillance

The psychology of monitoring is the dimension most often neglected in technical work yet most consequential for data quality. The meta-analytic evidence is clear that the presence of monitoring elevates strain largely irrespective of its characteristics, with no compensating performance gain [12]. Cognitive workload, best captured by the NASA Task Load Index across its six sub-scales [46], can rise through attentional diversion, performance pressure, dual-task interference and uncertainty management. Importantly, when monitoring delivers real-time, actionable ergonomic feedback rather than passive observation, the workload increase may be offset by reduced physical demand and improved performance — implying that acquisition systems should be engineered to return immediate value to the worker, converting a cognitive burden into a cognitive resource.

Trust and privacy concern complete the picture. Technology trust — a willingness to be vulnerable to a system on the basis of positive expectations [47] — is sensitive to transparency about what is collected, how it is processed and what it influences; privacy concern is its principal antecedent and tends to be higher where labour protections are weaker. Table 5 summarises these dimensions and their governance implications.

Table 5 Psychological dimensions of monitoring and their governance implications

Dimension	Instrument	Direction of effect	Governance implication
Surveillance perception	Purpose/fairness/control/benefit sub-scales	Punitive framing worsens strain; supportive framing neutral-to-positive	Frame monitoring as protection and development; ensure procedural justice
Cognitive workload	NASA-TLX (six sub-scales)	Passive monitoring raises load; active feedback can offset it	Provide real-time ergonomic feedback; minimise attentional diversion
Technology trust	Adapted trust scales	Opaque systems lower trust; transparency raises it	Maximise transparency; grant data access and control
Privacy concern	Adapted IUIPC	Amplified where protections are weak	Apply GDPR-equivalent protection regardless of jurisdiction; anonymise at source

Note. Synthesised from [12], [46], [47] and [26].

4.5. Tacit-knowledge capture and digital-twin applications

Tacit knowledge — the intuitive, hard-to-articulate expertise embedded in skilled manual work — is the principal differentiator between novice and expert operators [48, 49]. Its digitisation through Physical AI acquisition is both an opportunity and a hazard: capturing expert motion can accelerate skill transfer and preserve institutional knowledge, yet it raises questions of ownership, fair compensation and the risk of de-skilling. Worker (or operator) digital twins combine kinematic, biomechanical and behavioural models to enable predictive ergonomic assessment and personalised training [50]. Their fidelity, however, depends on acquisition conditions: data gathered from stressed or surveilled workers risks encoding a corrupted twin that reproduces sub-optimal performance, particularly where monitoring induces defensive, rigid movement in place of natural expertise. Governance that preserves rather than suppresses authentic performance is therefore a precondition for high-fidelity twins.

4.6. Multi-criteria decision-making for manufacturing safety

Three methods recur in manufacturing risk assessment and are integrated in the proposed engine. The Best-Worst Method (BWM) elicits criteria weights through two reference comparisons — best-to-others and others-to-worst — requiring only $2n-3$ comparisons rather than the $n(n-1)/2$ of pairwise approaches, with a built-in consistency guarantee [51]. Its fuzzy extension, building on fuzzy-set theory [52], represents linguistic preferences as triangular fuzzy numbers and derives weights via optimisation, accommodating the vagueness of expert judgement and typically achieving lower inconsistency than crisp BWM [53]. Recent bibliometric reviews confirm the method's rapid uptake and its frequent integration with other techniques [54].

Bayesian networks complement weighting by modelling conditional dependencies among risk factors and outcomes through a directed acyclic graph, supporting predictive inference, intervention simulation and root-cause analysis [55]. Fuzzy FMEA extends classical failure-mode analysis by replacing crisp severity, occurrence and detection ratings with fuzzy numbers, producing risk-priority numbers that better reflect assessment uncertainty [56]. Section 6.3 details how the three are sequenced into a single pipeline.

4.7. Ethical AI governance frameworks

Governance instruments have proliferated but address physical, worker-derived data only partially. The EU AI Act (Regulation 2024/1689), which entered into force on 1 August 2024, adopts a risk-based architecture; AI used to monitor and evaluate worker performance and behaviour falls within the high-risk category, with the full suite of obligations — risk management, data governance, human oversight, transparency and bias testing — becoming enforceable for employment-related systems from 2 August 2026 [57]. The Act also prohibits certain workplace practices outright: from 2 February 2025, emotion recognition in the workplace and biometric categorisation by sensitive attributes are banned, with penalties for prohibited practices reaching up to €35 million or 7% of global annual turnover [58]. Principle-based instruments such as the IEEE Ethically Aligned Design framework and the OECD AI Principles add valuable normative anchors — notably data agency and accountability — but offer limited operational guidance for manufacturing [59, 60].

The governance gap is most acute in developing economies, where labour-intensive manufacturing concentrates and where regulation of worker monitoring data is nascent. The risk is the emergence of data colonies in which workers generate training data, without compensation or consent, for systems that may ultimately displace them. Physical AI Data Governance is proposed precisely to close this gap by integrating technical standards, organisational policy and regulatory requirements designed for physical, worker-derived data.

5. Research gap analysis

5.1. Dimensional gap assessment

Although individual dimensions — vision accuracy, ergonomic validity, psychological measurement and governance design — have each received attention, their intersections remain under-explored. Figure 3 maps six research domains against six assessment dimensions on a 0-5 coverage scale, derived from the synthesis. Technical capability is well covered across domains; psychological impact, worker well-being and ethical governance are consistently weak; and the full intersection — the ideal of integrated Physical AI Data Governance — attains only a low average coverage. This intersectional deficit is the primary target of the framework.

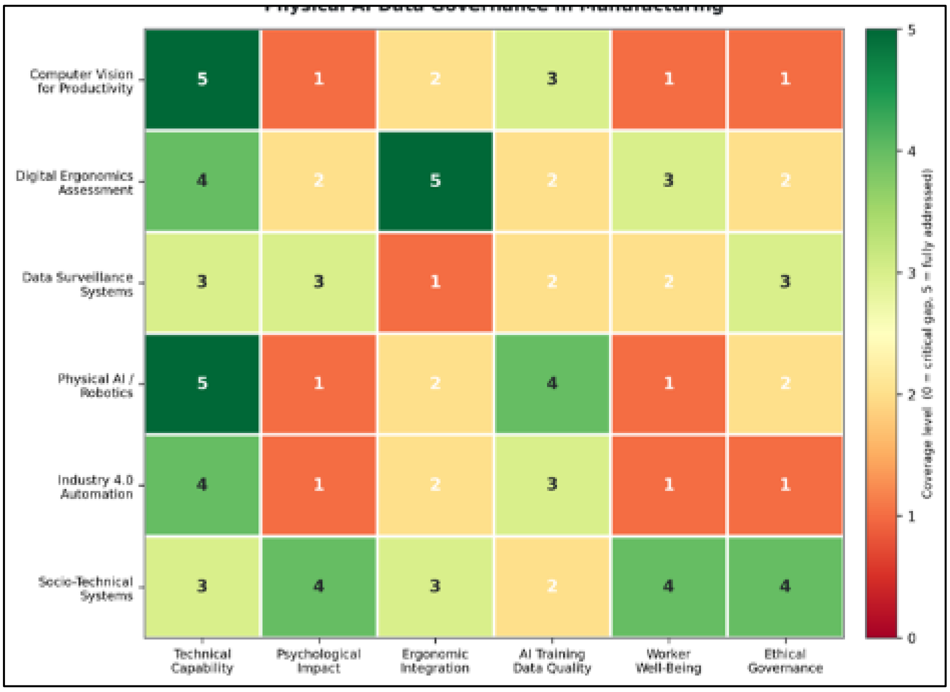

Figure 3 Research-gap matrix across six domains and six dimensions; lower scores denote critical gaps

5.2. The cybersecurity-humanity paradox

Physical AI data is simultaneously a high-value security asset and an intimate record of the human body. Aggregated motion data can reveal proprietary processes and production rates, and biometric motion signatures can enable identification and tracking beyond the workplace [11]. The conventional security response — encryption, access control, centralisation — tends to reduce worker transparency and control, while the human-centred imperative of agency, consent and benefit-sharing can sit awkwardly with uniform security enforcement. The review terms this tension the cybersecurity-humanity paradox and argues that it is resolvable only by integrating security and human-centred design from the outset, through four principles: privacy-by-design, differential privacy, federated learning, and worker data cooperatives that negotiate usage terms on workers' behalf.

5.3. Scalability challenges for SMEs

SMEs constitute the large majority of manufacturing enterprises and employment yet face disproportionate barriers — technical (infrastructure, expertise, integration), financial (substantial total cost of ownership relative to thin margins), and organisational (limited management capacity and worker representation, and supply-chain pressure to demonstrate compliance without resources to implement it genuinely) [2]. The result is a governance divide in which protection correlates inversely with enterprise size. The framework addresses this through open-source governance templates, shared-infrastructure cooperative models and tiered implementation pathways, detailed in Section 7.3.

6. The socio-technical Physical AI data governance framework

6.1. Architecture and components

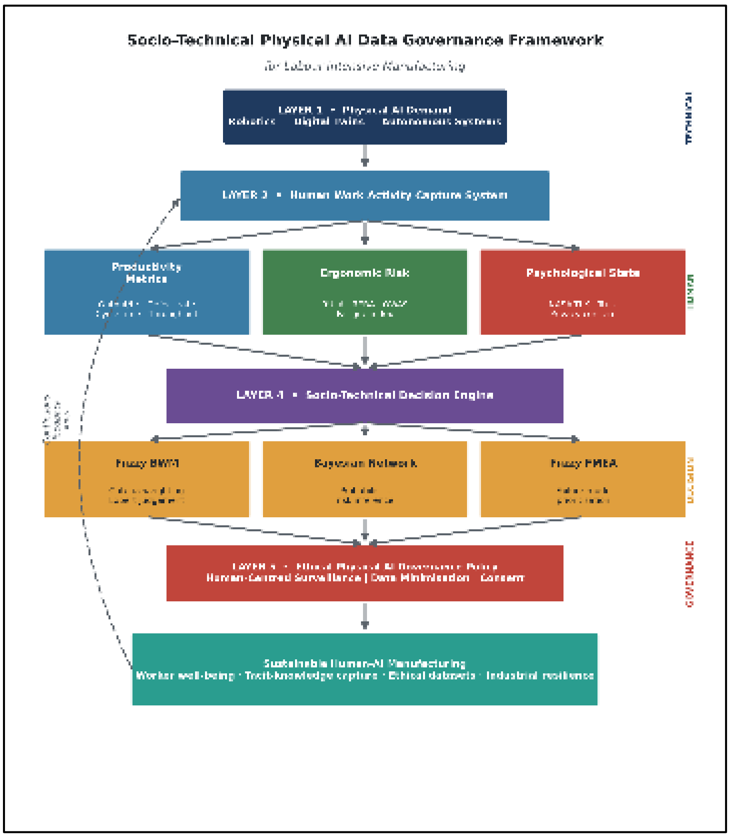

Figure 4 The five-layer Socio-Technical Physical AI Data Governance Framework, with continuous feedback from outcomes to capture design

The framework integrates five hierarchical layers into a system that jointly optimises dataset quality, worker well-being and ethical compliance (Figure 4). Layer 1, Physical AI Demand, establishes the strategic context — the specific data requirements of robotics, digital twins and autonomous systems — while insisting that acquisition serve worker interests. Layer 2, the Human Work Activity Capture System, integrates three parallel streams: productivity metrics, ergonomic risk assessment, and psychological-state monitoring, synchronised by timestamp and worker-identification protocols. Layer 3, Multi-Dimensional Risk Assessment, fuses these streams while modelling their interdependencies — for example, that elevated ergonomic risk predicts higher cognitive load, and that low trust predicts data-quality degradation — and identifies hot spots where several risks coincide.

Layer 4, the Socio-Technical Decision Engine, applies the integrated Fuzzy BWM-Bayesian-network-Fuzzy FMEA methodology (Section 6.3) to convert risk assessment into prioritised governance decisions: protocol modifications, ergonomic interventions, psychological-support measures and policy adjustments. Layer 5, the Ethical Physical AI Governance Policy, establishes the normative boundary — a human-centred surveillance policy, ethical data-collection guidelines, and a data-governance regime covering ownership, benefit-sharing, third-party sharing and cross-border transfer — conceived as a living framework that evolves through worker, regulator and technical feedback.

6.2. Variable classification and operationalisation

The framework operationalises assessment through technical, ergonomic and psychological variables, with corporate-strategy alignment as a mediator and sustainable human-AI manufacturing performance as the dependent construct. Technical variables comprise productivity metrics (output per hour, defect rate, cycle time, throughput) and data-quality indicators (motion completeness, tracking accuracy, sensor reliability, coverage). Ergonomic variables comprise digital-ergonomics scores (RULA, REBA, OWAS, fatigue index) and wearable-derived measures (posture-deviation angle, repetition frequency, force exertion, vibration exposure). Psychological variables comprise cognitive workload (NASA-TLX and its mental- and temporal-demand sub-scales) and surveillance perception (trust, privacy concern, perceived fairness, technology acceptance). Each is operationalised with a validated instrument and an explicit data source; the full measurement specifications appear in Appendix B.

6.3. Integrated methodology: Fuzzy BWM - Bayesian network - Fuzzy FMEA

The decision engine sequences three complementary methods into a single pipeline (Figure 5). Stage 1 applies Fuzzy BWM to establish criteria weights: experts identify the best and worst criteria, compare the remainder against these anchors using linguistic terms mapped to triangular fuzzy numbers, and the resulting preference vectors are solved as an optimisation that minimises the maximum deviation from consistency before defuzzification and aggregation [51, 53]. Stage 2 uses a Bayesian network to propagate evidence, so that high-weight criteria exert proportionate influence on outcome probabilities, and to simulate interventions and identify the most probable causes of adverse outcomes [55]. Stage 3 applies Fuzzy FMEA to prioritise specific failure modes — ergonomic, psychological, technical and security — by computing and ranking fuzzy risk-priority numbers [56].

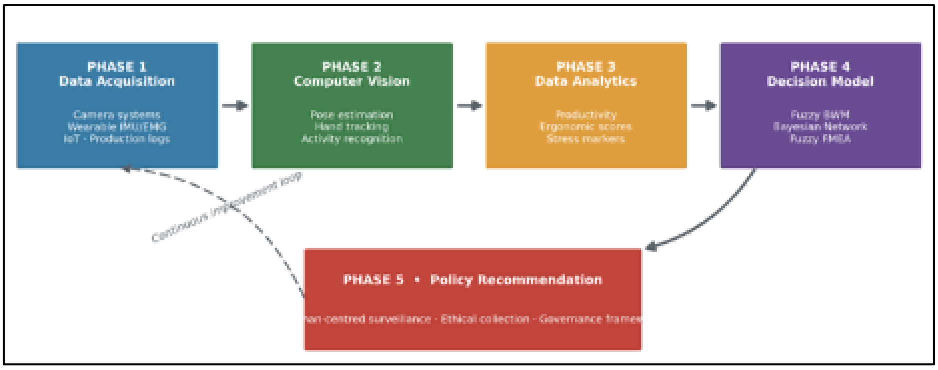

Figure 5 The integrated five-phase methodology, from data acquisition to policy recommendation, with a continuous-improvement loop

This sequencing ensures that decisions are at once strategically aligned (reflecting weighted organisational priorities), evidence-based (grounded in probabilistic models rather than intuition) and operationally actionable (yielding prioritised failure modes with assigned interventions). An illustrative Fuzzy BWM weighting for five governance criteria — with ergonomic-risk reduction emerging as the highest priority — is shown in Figure 6 and detailed in Appendix C.

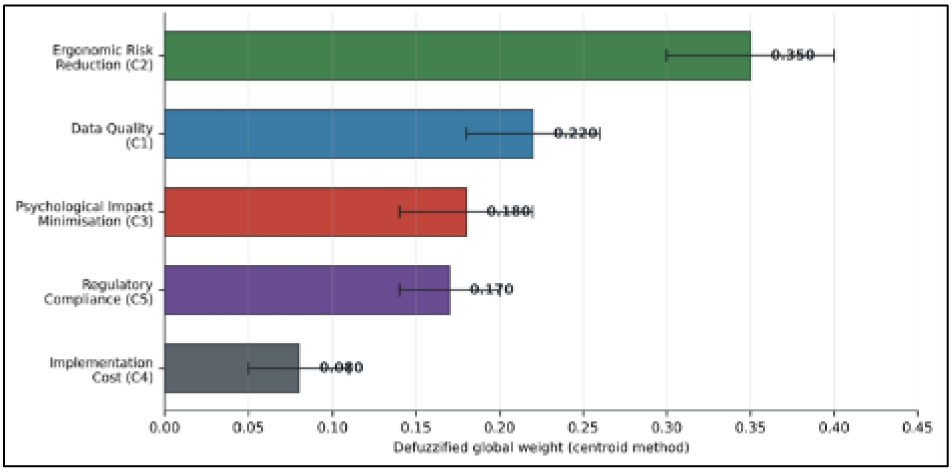

Figure 6 Illustrative Fuzzy BWM criteria weights for a worker-monitoring protocol decision (consistency ratio xi* = 0.042)

7. Discussion

7.1. Theoretical implications

The framework contributes across four domains. For industrial engineering, it re-conceptualises the worker-data relationship: in the Physical AI era, workers are simultaneously production factors and data generators, implying a principle of data-generative work design in which processes are engineered to produce high-quality training data while preserving well-being. For human-factors engineering, it positions ergonomic assessment as a data-quality control rather than only an injury-prevention measure, since ergonomic conditions and data quality are causally intertwined. For AI ethics, it establishes Physical AI Data Governance as a distinct domain addressing continuous motion capture, biometric profiling and tacit-knowledge extraction — challenges that digital-AI ethics frameworks do not fully reach. For socio-technical systems theory, it operationalises joint optimisation in AI-mediated manufacturing, demonstrating that technical and social objectives can be made synergistic rather than merely balanced.

7.2. Practical implications for industry

For enterprise management, the framework suggests a tiered approach that begins with non-intrusive productivity metrics and adds ergonomic and psychological monitoring only after trust is established; the establishment of worker data councils; investment in closed-loop feedback that returns tangible benefit; periodic governance audits; and data-contribution recognition mechanisms. For technology vendors, it sets design requirements: privacy-by-design with edge anonymisation, transparent explanations of how monitoring interprets movement, modular and interoperable systems, open data standards, and recognised security certification. For worker representatives, it offers a bargaining frame around data-ownership clauses, revocable informed consent, independent auditing, data minimisation and benefit-sharing. For regulators, it provides a foundation for Physical-AI-specific standards consistent with the trajectory of the EU AI Act.

7.3. Policy recommendations

7.3.1. Organisational policy

- Human-centred surveillance policy: justify all monitoring by documented operational need rather than generalised productivity enforcement, communicated transparently and reviewed annually.
- Informed-consent protocol: obtain explicit, revocable consent per use case, specifying data collected, processing, access, retention, benefits and withdrawal procedure.
- Data minimisation and anonymisation: limit collection to the strictly necessary; anonymise at the earliest stage; store identifier mappings separately under restricted access.
- Retention limitation and access rights: retain data only for the minimum necessary period with automatic deletion; grant workers access, explanation and correction rights.
- Benefit-sharing: demonstrate tangible worker benefit — documented ergonomic improvement, skill development and fair recognition for data contribution.

7.3.2. Industry standards

- Physical AI data-quality standards (motion completeness, tracking accuracy, mandatory ergonomic metadata, demographic-diversity requirements to limit algorithmic bias).
- Third-party ethical-collection certification, supply-chain transparency requirements for large buyers, and worker data-cooperative models adapted from agricultural precedents.

7.3.3. National and international regulation

- Extend data-protection law to biometric motion data, force profiles and tacit-knowledge recordings as a special category; restrict cross-border transfer of raw worker data absent equivalent protection.
- Adopt anti-de-skilling protections (data-for-jobs), SME support programmes, and an ILO instrument on AI-mediated worker monitoring establishing minimum standards for consent, transparency, minimisation, access and benefit-sharing.

Future research directions

Eight priorities follow from the synthesis. First, cross-cultural validity of surveillance-perception measures, given that collectivist and individualist contexts may respond differently to identical monitoring. Second, long-term health consequences of continuous monitoring, which short studies cannot resolve and which warrant multi-year cohort designs. Third, algorithmic bias in Physical AI systems trained on demographically narrow worker populations, with attendant fairness metrics and inclusive-collection protocols. Fourth, economic valuation of worker-generated data to inform fair compensation and cooperative governance. Fifth, cybersecurity threat modelling specific to Physical AI — adversarial attacks on pose estimation, data poisoning and biometric spoofing — with appropriate countermeasures. Sixth, SME-specific governance optimised for low-cost sensing and minimal legal overhead. Seventh, worker agency and resistance, studied through participatory action research that treats workers as co-designers. Eighth, integration with emerging technologies — brain-computer interfaces, exoskeletons, augmented reality and decentralised data governance — each of which introduces distinct governance challenges.

8. Conclusion

This review has addressed a gap at the intersection of Physical AI, labour-intensive manufacturing and human-centred governance. Synthesising 187 sources, it develops the Socio-Technical Physical AI Data Governance Framework, which re-conceptualises manual workers as intentional Physical AI Data Generators and treats their tacit knowledge, ergonomic state and psychological experience as foundational data assets. Five conclusions stand out, stated with appropriate caution. Existing monitoring is technically capable but predominantly surveillance-oriented, neglecting the dimensions that determine both welfare and data quality. The psychological impact of monitoring is a modifiable design parameter rather than an inevitable cost. Ergonomic assessment, properly integrated, functions as a data-quality control as much as a safety measure. Existing AI-governance instruments do not yet reach the specificities of physical, worker-derived data, leaving regulatory vacuums most acute in developing economies. And the integration of Fuzzy BWM, Bayesian networks and Fuzzy FMEA provides a coherent engine for ergonomic-psychological-technical trade-offs.

The framework is conceptual and its principal limitation is the absence of empirical validation; the integrated methodology requires computational implementation and testing against real decision scenarios, and the variable taxonomy will require adaptation across industries and cultures. These limitations define the agenda: controlled field validation, open-source tooling for the methodology, cross-cultural testing and sustained policy advocacy. The transition from Industry 4.0 to Industry 5.0 is not merely a technological upgrade but a re-orientation that places human workers at the centre of production. By re-framing workers as intentional data generators, integrating ergonomic and psychological protection into data-quality management, and establishing governance principles that travel across scales and borders, the framework offers a pathway toward manufacturing that serves both technological progress and human dignity.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare no competing financial interests or personal relationships that could appear to influence the work reported in this paper.

Statement of informed consent

This study is a conceptual systematic literature review. No primary human-subjects data were collected; therefore, informed consent and ethical-approval requirements for human participants are not applicable. The search strategy, inclusion and exclusion criteria and quality-appraisal protocols are documented within the manuscript and appendices.

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Appendix A. Database coverage and screening

Table A1 Search and screening results by database

Database	Initial	After dedup.	Full-text	Final
Scopus	1,456	987	156	72
Web of Science	892	612	98	45
IEEE Xplore	678	456	74	38
ACM Digital Library	423	298	48	22
PubMed/MEDLINE	234	156	22	8
PsycINFO	164	104	14	2
Total	3,847	2,613	412	187

Appendix B Variable measurement specifications

Table B1 Operationalised measurement specifications for framework variables

Variable group	Indicator	Instrument / method	Data source
Technical - productivity	Output/hr; defect rate; cycle time; throughput	MES/ERP integration; SPC; CV task segmentation	Production and quality systems
Technical - data quality	Motion completeness; tracking accuracy; sensor reliability; coverage	Pose-estimation confidence; annotation validation; IoT health API	Vision/sensor pipeline logs
Ergonomic - digital	RULA; REBA; OWAS; fatigue index	Joint-angle calculation + scoring tables; EMG median-frequency analysis	CV pose or IMU/EMG data
Ergonomic - wearable	Posture-deviation angle; repetition frequency; force; vibration	IMU orientation; accelerometer peak detection; instrumented tools (ISO 5349)	Wearable sensor array
Psychological - workload	NASA-TLX total; mental/temporal demand	Post-task NASA-TLX questionnaire	Worker self-report
Psychological - perception	Trust; privacy concern; fairness; acceptance	Adapted trust scale; IUIPC; procedural-justice items; TAM	Worker self-report (periodic)

Appendix C. Illustrative Fuzzy BWM calculation

Consider five governance criteria for a new monitoring protocol: C1 data quality (technical), C2 ergonomic-risk reduction (ergonomic), C3 psychological-impact minimisation (psychological), C4 implementation cost (economic) and C5 regulatory compliance (legal). An expert panel selects C2 as best and C4 as worst, comparing the remaining criteria against these anchors using triangular fuzzy numbers (for example, equally important = (1,1,1); fairly more important = (3/2, 2, 5/2); absolutely more important = (7/2, 4, 9/2)). Solving the optimisation that minimises the maximum deviation from consistency, and defuzzifying by the centroid method, yields the weights below at a consistency ratio of xi *= 0.042 (acceptable, xi* < 0.1).

Table C1 Fuzzy and crisp criteria weights (illustrative)

Criterion	Fuzzy weight (l, m, u)	Defuzzified weight	Rank
C2 Ergonomic-risk reduction	(0.30, 0.35, 0.40)	0.350	1
C1 Data quality	(0.18, 0.22, 0.26)	0.220	2
C3 Psychological-impact minimisation	(0.14, 0.18, 0.22)	0.180	3
C5 Regulatory compliance	(0.14, 0.17, 0.20)	0.170	4
C4 Implementation cost	(0.05, 0.08, 0.11)	0.080	5

Appendix D. Comparative impact assessment

As an illustrative elicitation, an expert panel rated traditional surveillance against the proposed human-centred framework across six dimensions on a five-point scale. The exercise is conceptual rather than empirical and is reported to motivate hypotheses for subsequent field validation; the values should not be read as measured outcomes. The proposed configuration is rated higher across all dimensions, with the largest differences in ethical compliance and ergonomic improvement, and a first-year cost penalty that reverses over a five-year horizon once turnover, injury and litigation costs are considered (Figure 7).

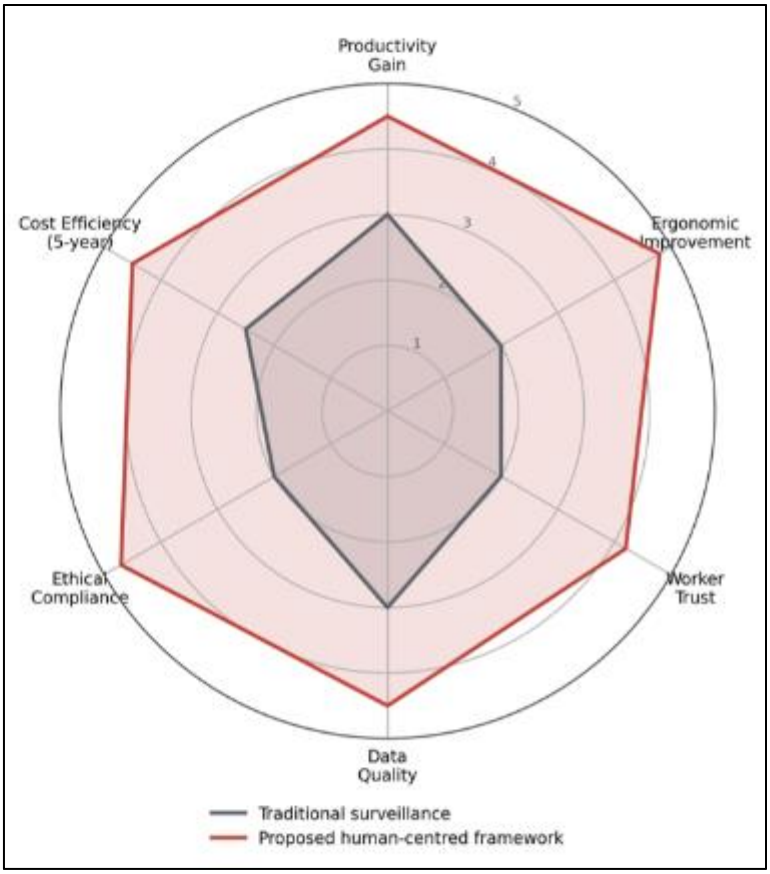

Figure 7 Illustrative comparative impact assessment across six dimensions (traditional surveillance versus the proposed human-centred framework).

Table D1 Illustrative comparative impact scores (five-point scale)

Dimension	Traditional	Proposed	Difference
Productivity gain	3.0	4.5	+1.5
Ergonomic improvement	2.0	4.8	+2.8
Worker trust	2.0	4.2	+2.2
Data quality	3.0	4.5	+1.5
Ethical compliance	2.0	4.7	+2.7
Cost efficiency (5-year)	2.5	4.5	+2.0