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Review Article

# Toward a Unified Ergonomic Risk Index for Manual Loading and Unloading: An Integrated Multi-Domain Framework

**Akhmadbek Jalilov[1, *], Narziev Shovkiddin Murtozaevich[2]**

[1]Department of Labour Safety Research, Institute for Poverty Reduction and Labour Market Research, Tashkent, Uzbekistan

[2]Department of Mathematics and Natural Sciences, Renaissance University, Tashkent, Uzbekistan

## Abstract

Manual loading and unloading of raw materials and semi-finished products remains one of the most injury-intensive operations in manufacturing and logistics, and it continues to drive a disproportionate share of work-related musculoskeletal disorders. Established assessment tools — RULA, REBA, OWAS, and the NIOSH lifting equation — each capture a single facet of exposure, and recent attempts to combine them through multi-criteria decision-making have concentrated almost exclusively on the biomechanical domain, leaving physiological strain, cognitive workload, and environmental stressors outside the analytic frame. This fragmentation prevents safety practitioners from ranking heterogeneous hazards on a common scale and from targeting interventions where composite risk is highest. This article develops the Integrated Human-factor and Ergonomic-load assessment Framework (IHEF), a five-layer architecture that normalises biomechanical, physiological, cognitive, and environmental sub-scores and fuses them into a single Composite Risk Index through Analytic Hierarchy Process weighting, before linking the index to a hierarchy-of-controls decision layer and a continual-improvement feedback loop. The framework further triangulates the three classical load-limit criteria and specifies a reproducible task-decomposition and data-reduction procedure for multi-task jobs. A matched-plant validation protocol, complete with an a-priori statistical-power justification, is presented to demonstrate feasibility in industrial practice. The framework offers safety managers a transparent, auditable basis for prioritising ergonomic interventions across competing hazard domains. Its originality lies in extending multi-criteria ergonomic assessment beyond posture to a genuinely multi-domain composite index tailored to loading and unloading work. No empirical results are reported; all numerical values are planning parameters awaiting validation.

## Keywords

Manual Materials Handling, Ergonomic Risk Assessment, Composite Risk Index, Analytic Hierarchy Process, Human Factors, Occupational Safety, Musculoskeletal Disorders, Work-system Design

*Correspondence: Akhmadbek Jalilov (ahmadbekhfx555@gmail.com)

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# 1. Introduction

Few industrial operations expose workers to as broad a spectrum of physical demand as the manual loading and unloading of raw materials and semi-finished products. The task combines heavy lifting, lowering, carrying, pushing, and pulling, often at awkward reach distances and under production-driven time pressure, and it consequently occupies a persistent place at the top of occupational injury statistics [1]. Work-related musculoskeletal disorders (WMSDs) arising from these operations impose a documented economic burden that recent official estimates place in the tens of billions of dollars annually for manufacturing and warehousing alone [2]. In the metals sector, where profiles of considerable length and mass must be moved by hand, the exposure is compounded by grip difficulty and load asymmetry, so that the nominal weight of an item understates the true biomechanical demand placed on the handler, a point long established in occupational biomechanics [33].

The scientific response to this problem has produced a rich toolbox of assessment instruments, yet that toolbox is fragmented by construction. Postural methods such as RULA and REBA quantify the geometry of working posture [3, 4]; the NIOSH Revised Lifting Equation estimates spinal compressive load for a defined lift [5]; the Snook-Ciriello psychophysical tables express acceptable weights and forces as population percentiles [6]; physiological criteria bound whole-body workload at a sustainable fraction of aerobic capacity [7]; and NASA-TLX captures the cognitive load that accompanies vigilance and coordination in team handling [8]. Each instrument answers a different question, and each was validated against a different criterion. A practitioner who applies only one of them therefore obtains a partial picture of a manifestly multi-dimensional exposure.

A natural remedy is to combine several instruments within a single decision-analytic structure, and the past decade has seen multi-criteria decision-making (MCDM) methods, most prominently the Analytic Hierarchy Process (AHP), applied to exactly this end [9-14]. These contributions have advanced the field considerably; the framework of Cimino and colleagues for container-terminal operators, for instance, demonstrated convincingly that AHP can rank handling macro-activities and prioritise interventions [9]. Nevertheless, a close reading of this literature reveals a systematic narrowing: the criteria that enter the hierarchy are, in the overwhelming majority of cases, biomechanical or postural. Physiological strain and cognitive workload are acknowledged in the introductions of these papers and then omitted from their models. The result is a sophisticated weighting apparatus applied to an impoverished set of inputs.

This omission matters for three reasons. First, the binding constraint on a handling task shifts with its tempo: at low frequency the biomechanical criterion governs, whereas at high frequency the physiological criterion becomes decisive, and a model blind to the latter will misclassify precisely the fast, repetitive jobs that dominate loading bays. Second, the transition to human-centric manufacturing under the Industry 5.0 agenda has moved operator wellbeing from a compliance afterthought to a design objective [20, 21], and a wellbeing objective cannot be served by an index that ignores mental workload. Third, safety managers who must allocate finite budgets across competing hazards need those hazards expressed on one commensurable scale; a posture score, a heart-rate reserve, and a workload rating cannot be compared until they are fused.

The present work responds to this gap. It develops the Integrated Human-factor and Ergonomic-load assessment Framework (IHEF), a layered architecture that fuses biomechanical, physiological, cognitive, and environmental exposure into a single Composite Risk Index and links that index to control selection and continual improvement. Rather than proposing yet another posture tool, the framework organises existing, validated instruments into a coherent whole and adds the aggregation logic that the loading and unloading task demands.

Two research questions structure the contribution:

1) How can biomechanical, physiological, cognitive, and environmental exposure be fused into a single, auditable ergonomic risk index for manual loading and unloading operations?
2) How can such an index be validated in industrial practice, and what study design would establish its predictive value for injury?

The paper is deliberately a framework-and-protocol contribution. It specifies the architecture, the aggregation mathematics, and a pre-registrable validation design, but it reports no empirical results, and every numerical value it contains is a planning parameter or a prior estimate awaiting validation. The novelty is therefore conceptual and methodological: to our knowledge, this is the first ergonomic MCDM framework for loading and unloading that treats physiological and cognitive load as first-class criteria alongside biomechanical exposure, and that embeds the resulting index in the Plan-Do-Check-Act logic of a managed work system. The remainder of the paper reviews the relevant literature critically, specifies the framework and its methodology, presents the validation protocol, and discusses the theoretical, practical, and policy implications.

# 2. Literature Review

The literature relevant to a multi-domain index falls into four streams: the classical assessment instruments, their known validity limits, the MCDM attempts to integrate them, and the digital and human-centric technologies now reshaping the field. Each is examined in turn, with attention to inconsistencies and unresolved problems rather than mere summary.

## 2.1. The Classical Instruments and Their Single-domain Character

The observational posture methods remain the workhorses of applied ergonomics. RULA and REBA convert joint angles into ordinal grand scores and action levels [3, 4], and their appeal lies in low cost and speed. Their weaknesses are equally well established: they are observer-dependent, they compress continuous load into coarse categories, and they say nothing about the metabolic or cognitive cost of a task. The NIOSH equation is more mechanistic, translating lift geometry into a Lifting Index anchored to a spinal-compression criterion [5], but it was designed for symmetric, single-task lifting and degrades when applied to the multi-task, asymmetric reality of a loading bay, where cumulative and dynamic spinal loading mechanisms dominate causation [34]. The psychophysical tradition, embodied in the Snook-Ciriello tables [6], is uniquely broad in covering push, pull, and carry as well as lift, yet its self-selection basis loses validity above roughly six lifts per minute, and verification studies show that short-trial acceptable weights overstate what is sustainable across a full shift [30, 31]. The multi-task lifting procedures codified in the NIOSH applications manual address part of this problem but do not extend to the physiological domain [41]. The physiological criterion complements these by bounding workload at a fraction of aerobic capacity [7], and it becomes the governing constraint precisely where the psychophysical method fails. No single instrument, in short, spans the task.

## 2.2. Validity and Reliability: An Unresolved Tension

A recurring and instructive inconsistency concerns the criterion validity of the observational methods. A recent in-vivo study compared OWAS and REBA action levels against measured joint loads at the spine, hip, and knee and found that, although the methods could distinguish broad load categories, identical action levels did not correspond to identical measured loads across lifting techniques [15]. This is a consequential finding: it implies that an intervention triggered by an action-level threshold may be mis-targeted, because the threshold conflates biomechanically distinct situations. The observation undermines any framework that treats a posture score as an interval-scaled quantity, and it motivates the normalisation approach adopted later in this paper, in which each instrument is referenced to its own validated action thresholds rather than assumed commensurable by fiat.

## 2.3. Multi-criteria Integration: Progress and Its Blind Spot

The MCDM literature represents the most direct precursor to the present work, and it merits detailed scrutiny. Cimino et al. applied AHP to container lashing and unlashing operations, mapping macro-activities and ranking them by ergonomic criticality, and explicitly noted the near-total absence of full ergonomic assessment procedures for such operations in both the scientific and the regulatory record [9]. Their contribution is important precisely because it formalises intervention prioritisation; yet the criteria feeding their hierarchy are posture-derived, and physiological and cognitive load do not enter the model. A parallel body of work has enriched the mathematics — fuzzy AHP to handle linguistic uncertainty [14], spherical-fuzzy and FUCOM-ARTASI hybrids for port operations [12], and imbalanced-data prediction frameworks [13] — but the enrichment has been almost entirely on the aggregation side, not the input side. The one notable exception is the ergonomic index of Rezvanizadeh and colleagues, which explicitly combined physical, cognitive, and environmental components into a composite [11]; that study, however, addressed general workplaces rather than materials handling, did not incorporate the load-limit criteria specific to lifting, and stopped short of a control-selection or validation layer. The field thus exhibits a clear division of labour — sophisticated weighting on the one hand, multi-domain inputs on the other — that no single contribution has yet unified for loading and unloading work.

## 2.4. Digitalisation, Sensors, and the Human-Centric Turn

A fourth stream promises to relax the measurement bottleneck that has historically constrained multi-domain assessment. Inertial and vision-based systems now compute the NIOSH Index online from body-worn or camera data [16, 19], deep networks estimate REBA scores directly from images [17], and electromyographic armbands classify lift-lower tasks and hand loads in the field [28]. Systematic reviews of wearable assessment in healthcare and industry confirm both the trajectory and its immaturity [18], and an official technology assessment cautions that the evidence base for exoskeletons and related wearables remains thin despite their commercial momentum [2]. Systematic evidence mapping of occupational exoskeletons reaches a similar verdict [23], and studies of their adoption in manufacturing and construction show that uptake depends as much on organisational acceptance as on biomechanical efficacy [24, 25]; efforts to connect exoskeleton effectiveness to quantified ergonomic risk [26] and to physical fatigue measured by wearable sensors and deep learning [27] point toward the multi-domain evidence this framework is designed to accommodate. These technologies matter for the present framework because they make continuous, multi-domain data acquisition plausible: heart-rate reserve, posture, and even proxies for cognitive load can increasingly be captured in parallel, as automated sensor-based assessment frameworks for Industry 5.0 now demonstrate [29]. The human-centric manufacturing agenda that motivates their deployment [20, 21], and the axiomatic-design and worker-centred redesign methods emerging alongside them [22], reframe ergonomic assessment as an input to work-system design rather than a retrospective audit. A framework fit for this

era must therefore be not only multi-domain but also decision-oriented and iterative.

## 2.5. Synthesis and Research Gap

Table 1 arranges the assessment paradigms against the exposure domain each captures and the limitation each carries for loading and unloading. Read as a whole, the literature supports three conclusions. The instruments are individually validated but individually partial, a pattern confirmed by recent scoping evidence on the uneven coverage of risk factors across assessment tools [42]; their integration through MCDM has matured on the weighting side while remaining biomechanically narrow on the input side; and the digital turn now makes genuine multi-domain data acquisition feasible without resolving how the resulting heterogeneous signals should be fused into an actionable index. The gap addressed by this paper is therefore specific and defensible: no existing framework for manual loading and unloading fuses biomechanical, physiological, cognitive, and environmental exposure into a single validated risk index linked to control selection and continual improvement.

***Table 1.*** *Assessment paradigms for manual loading and unloading, the exposure domain each captures, and its principal limitation. Source: authors' synthesis of the cited literature.*

| Assessment paradigm | Representative tools | Exposure domain captured | Principal limitation for loading/unloading |
|---|---|---|---|
| Postural / biomechanical | RULA [3], REBA [4], OWAS | Working posture; segmental load | Single-task; no cognitive or physiological load; observer subjectivity [15] |
| Load-limit / biomechanical | NIOSH RLE [5] | Spinal compressive load per lift | Symmetric single-lift focus; weak at high frequency |
| Psychophysical | Snook-Ciriello tables [6] | Worker-accepted maximum weight/force | Unreliable above ~6 lifts/min; may exceed physiological limit |
| Physiological | %HRmax; energy expenditure [7] | Whole-body metabolic strain | Costly field measurement; large inter-individual variance |
| Cognitive | NASA-TLX [8] | Mental workload | Rarely integrated with physical exposure |
| MCDM-integrated | AHP / fuzzy-AHP [9, 11-14] | Weighted combination of criteria | To date dominated by biomechanical criteria only |

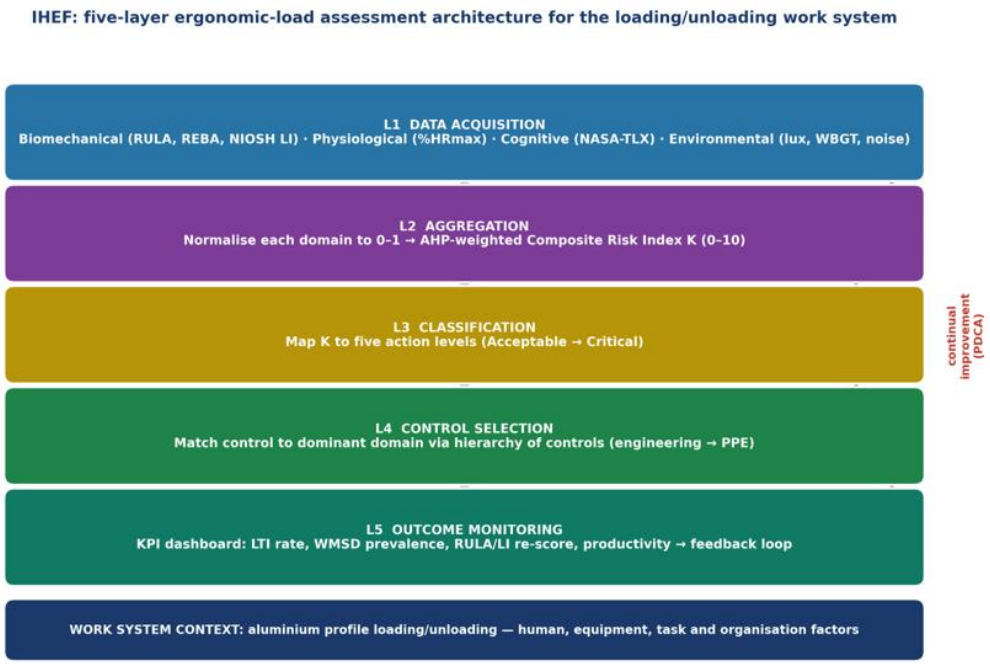


***Figure 1.*** *The IHEF five-layer architecture embedded in the loading/unloading work system, with a continual-improvement (PDCA) feedback loop. Figure prepared by the authors.*

*Table 2. The five layers of the IHEF framework and their inputs and outputs. Source: authors.*

| Layer | Function | Instruments / inputs | Output |
|---|---|---|---|
| L1 Data acquisition | Capture exposure in four domains | RULA, REBA, NIOSH LI [3-5]; %HRmax [7]; NASA-TLX [8]; lux, WBGT, noise | Domain sub-scores (0-1) |
| L2 Aggregation | Fuse domains into one index | AHP-weighted sum of normalised sub-scores [10] | Composite Risk Index K (0-10) |
| L3 Classification | Map K to action level | Five thresholds (Acceptable → Critical) | Risk level 1-5 |
| L4 Control selection | Match control to dominant domain | Hierarchy of controls [37] | Prioritised control plan |
| L5 Outcome monitoring | Track KPIs and re-trigger | LTI rate, WMSD prevalence, RULA/LI re-score, productivity | Feedback to L1 (PDCA) |

## 3. The IHEF Framework

Building on the gap identified above, the IHEF is specified as a five-layer architecture (Figure 1; Table 2). The design principle is separation of concerns: measurement, aggregation, classification, control, and monitoring are distinct layers, so that each can be revised — for instance, as sensor technology matures — without disturbing the others. This layered separation reflects the systems view of ergonomics as the design of human-compatible systems [35].

### 3.1. Layer 1: Multi-domain Data Acquisition

The first layer captures exposure in four domains using validated instruments (Table 3). Biomechanical load is scored with RULA, REBA, and the NIOSH Lifting Index [3-5]; physiological strain is monitored as percentage of heart-rate reserve, a field-validated proxy for metabolic load [7, 32]; cognitive workload is measured with NASA-TLX [8]; and environmental stressors are captured as illuminance, wet-bulb globe temperature, and noise. A hybrid acquisition procedure is prescribed for the NIOSH parameters, whose geometric multipliers are difficult to read from video: horizontal, vertical, travel, and asymmetry values are measured in person, while frequency and posture angles are coded from synchronised video, preserving metric accuracy without sacrificing repeatability.

*Table 3. Layer 1 sub-indicators, their normalisation references, and directionality. Source: authors, based on the cited instrument standards.*

| Domain | Sub-indicator | Normalisation reference | Direction |
|---|---|---|---|
| Biomechanical | RULA/REBA grand score; NIOSH LI | Action-level thresholds [3-5] | Higher = worse |
| Physiological | Mean%HRmax over shift | 45% sustainable-work limit [7] | Higher = worse |
| Cognitive | End-of-shift NASA-TLX | 0-100 scale [8] | Higher = worse |
| Environmental | Composite of lux, WBGT, noise | ISO/EN threshold limit values | Deviation = worse |

### 3.2. Layer 2: Normalisation and AHP Aggregation

Each sub-indicator is first normalised to the unit interval by reference to its own validated action threshold rather than to an arbitrary common scale, a choice motivated directly by the criterion-validity problem documented in Section 2.2 [15]. The four domain sub-scores are then fused into a single Composite Risk Index K on a 0-10 scale by a weighted sum, with weights derived through the Analytic Hierarchy Process from expert pairwise comparisons [10]. Formally, for worker-shift j, K_j equals ten times the sum over the four domains d of w_d times s_dj, where s_dj is the normalised sub-score and w_d is the AHP weight, with the weights constrained to sum to unity and the pairwise-comparison consistency ratio required to fall

below 0.10. This construction makes the index transparent and auditable: the contribution of every domain to the final score is explicit, and the weights themselves are open to scrutiny and revision.

*Note. Provisional prior weights (biomechanical 0.40, physiological 0.25, cognitive 0.20, environmental 0.15) are used only to illustrate the arithmetic. They are estimates to be re-derived empirically in the validation study and must not be treated as established values.*

### 3.3. Layers 3-5: Classification, Control, and Continual Improvement

Layer 3 maps K to five action levels, from Acceptable to Critical, with thresholds calibrated during validation. Layer 4 selects controls matched to the domain that contributes most to K, following the hierarchy of controls embedded in ISO 45001 [37]: a job dominated by biomechanical load is routed to engineering redesign or mechanical assistance, whereas one dominated by physiological strain is routed to work-rest scheduling. Layer 5 monitors outcome indicators and re-triggers assessment when they deteriorate, closing a Plan-Do-Check-Act loop that binds the framework to the continual-improvement logic of a managed safety system and distinguishes it from one-shot assessment tools; the feedback structure also embodies the adaptive, resilience-oriented view of safety management [36].

### 3.4. Load-limit Triangulation and Task Decomposition

Within Layer 1, the three classical load-limit criteria are triangulated rather than treated as substitutes: the biomechanical criterion governs heavy single lifts, the psychophysical tables cover push, pull, and carry, and the physiological criterion binds high-frequency sustained work above roughly six lifts per minute [6, 7]. Because a handling job comprises several tasks, an explicit data-reduction rule (Figure 2) decomposes the job, scores each task, retains task-level peaks alongside a job-level composite index, and aggregates a time-weighted exposure to worker-shift level for entry into Layer 2.

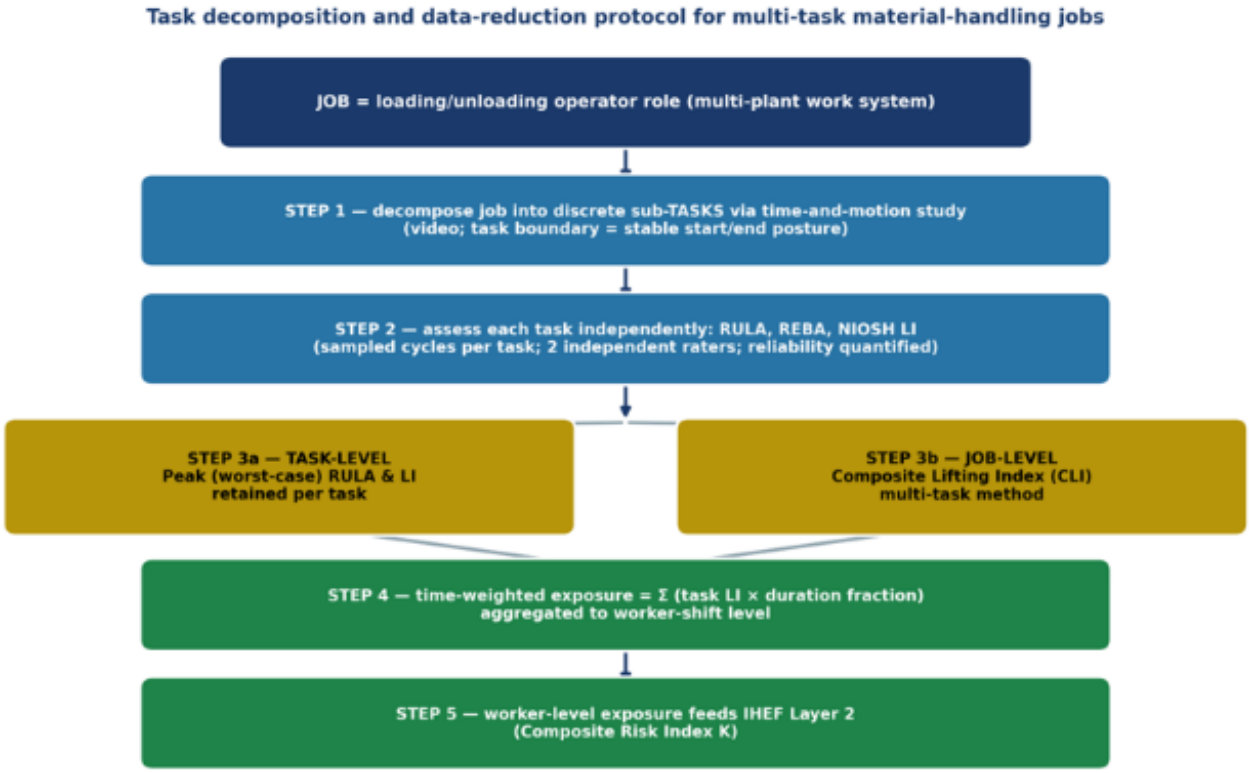


***Figure 2.*** *Task-decomposition and data-reduction protocol feeding the IHEF Composite Risk Index. Figure prepared by the authors.*

## 4. Validation Methodology

Having specified the framework, we now set out the methodology by which its measurement properties and predictive value would be established. The design follows SPIRIT protocol conventions [39] and STROBE reporting principles for the observational components [40]; it has not been executed, and ethical approval and prospective registration would precede any data collection. Table 4 summarises the planned parameters.

*Table 4. Planned parameters of the matched-plant validation study. All values are planning parameters, not results. Source: authors.*

| Parameter | Planned value | Basis |
|---|---|---|
| Design | Prospective matched-plant quasi-experiment | Plant-level engineering controls preclude individual randomisation |
| Plants / arms | 4 plants, 2 matched pairs | Matched on scale, workforce, baseline injury rate |
| Target sample | ≈ 180 workers per arm | Power analysis (see text) |
| Primary outcome | Lost-time injury rate / 1,000 worker-months | Person-time denominator from payroll |
| Follow-up | 12-month baseline + 24-month follow-up | Difference-in-differences estimation |
| Reliability targets | Cohen's $\kappa \geq 0.75$; ICC $\geq 0.80$ | Pre-specified acceptance thresholds |
| Primary validation | Predictive validity of Composite Risk Index K | Cox model; c-statistic vs single-domain models |

## 4.1. Design, Setting, and Sampling

A prospective matched-plant quasi-experimental design is proposed at four aluminium profile plants, matched in two pairs on production scale, workforce size, and baseline injury rate. Individual randomisation is infeasible because the candidate engineering controls operate at plant level; a difference-in-differences contrast between matched intervention and control plants, across a twelve-month baseline and a twenty-four-month follow-up, therefore carries the causal argument. All loading and unloading operators at the participating plants would be eligible, with exclusion limited to those unable to give informed consent.

## 4.2. Measurement, Reliability, and Validity

Before any outcome analysis, a measurement sub-study would quantify the reliability of every instrument, with pre-specified acceptance thresholds of Cohen's kappa at or above 0.75 for categorical scores and an intraclass correlation coefficient at or above 0.80 for continuous ones; instruments failing these thresholds would be retrained or replaced. Construct validity would be examined through the pattern of inter-domain correlations, and the criterion validity of the composite index would be tested against the injury outcome. The AHP weights would be re-derived from an expert panel, with the consistency ratio reported for every pairwise-comparison matrix.

## 4.3. Variables, Outcomes, and Statistical Analysis

The primary outcome is the lost-time injury rate per one thousand worker-months, computed on a person-time denominator drawn from payroll records. The primary exposure is the Composite Risk Index K; secondary variables include the individual domain sub-scores and standard covariates of age, tenure, and shift length. The causal effect of the IHEF-guided intervention would be estimated by difference-in-differences Poisson regression with a plant random effect. The central validation hypothesis — that K predicts injury better than any single domain score — would be tested with a multivariable Cox proportional-hazards model, comparing the composite against single-domain models by the concordance statistic and the net reclassification improvement. A sample of approximately one hundred and eighty workers per arm yields about eighty per cent power to detect an injury-rate ratio of 0.60 at a two-sided alpha of 0.05 over twenty-four months, assuming a baseline rate of twelve per thousand worker-months; this is a planning calculation, not a result. Analyses would be conducted in R, and the analysis code would be deposited alongside the protocol.

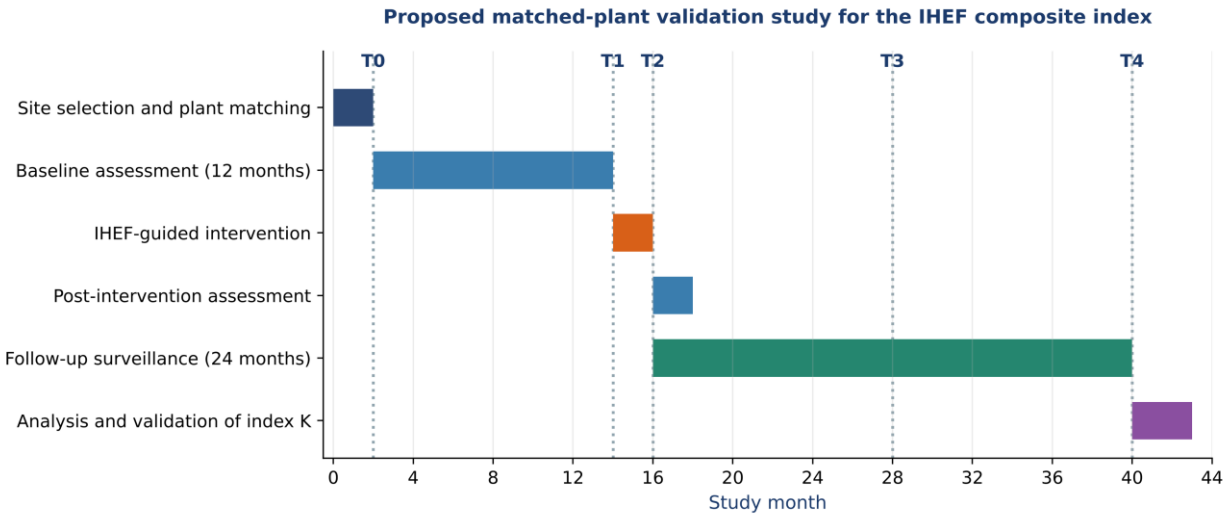


***Figure 3.*** *Proposed matched-plant validation study schedule in SPIRIT format; T0-T4 denote assessment timepoints. Figure prepared by the authors.*

### 4.4. Ethics

The planned study would be submitted for institutional ethics approval and registered prospectively before recruitment, with written informed consent obtained from all participants and de-identified data retained under a documented management plan. No data have been collected at the time of writing.

Generative AI assistance: during the preparation of this work the authors used a generative AI-assisted tool to support language editing and the drafting of figure layouts. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## 5. Expected Contributions and Discussion

Because the study reports no empirical results, this section discusses what the framework is expected to contribute and how it relates to prior work, rather than interpreting data. Three lines of contribution are anticipated.

### 5.1. Theoretical Contribution

The framework's primary theoretical move is to treat physiological and cognitive load as first-class criteria in an ergonomic MCDM model for materials handling, a step that the dominant biomechanically framed literature has not taken [9, 12-14]. In doing so it operationalises, for the loading and unloading task, the multi-component logic that Rezvanizadeh et al. advanced for general workplaces [11], while adding the load-limit triangulation and the control and monitoring layers that their index lacked. It thereby connects two previously separate conversations — the MCDM-weighting conversation and the multi-domain-index conversation — within a single architecture.

### 5.2. Practical and Industrial Implications

For practice, the composite index offers safety managers something the current toolbox withholds: a single, auditable number that ranks heterogeneous jobs on one scale and points, through Layer 4, to the class of control most likely to reduce it. This directly serves the intervention-prioritisation problem that motivated the container-terminal work of Cimino et al. [9], but across a wider set of hazards. The framework is also positioned for the digital instrumentation now entering industry: as online NIOSH and REBA estimation [16, 17, 19] and wearable physiological monitoring [28] mature, they can feed Layer 1 without altering the aggregation logic, aligning the framework with the human-centric ambitions of Industry 5.0 [20, 21], with worker-centred redesign methods [22], and with the broader shift in load-handling ergonomics documented for Industry 4.0 and 5.0 [43].

### 5.3. Policy Implications

At the policy level, an auditable composite index is congruent with the risk-based, management-system philosophy of ISO 45001 [37] and the manual-handling provisions of ISO 11228-1 [38], and it could give regulators a defensible basis for comparing ergonomic risk across enterprises. The persistent caution in official technology assessments about thin evidence for new ergonomic interventions [2] underscores the value of the framework's built-in validation and monitoring layers, which are designed precisely to generate the outcome evidence that such assessments find lacking.

### 5.4. Limitations

Several limitations qualify the contribution. The framework is a proposal awaiting empirical test; its weights, thresholds, and predictive value are all hypotheses. The reliance on AHP inherits that method's known sensitivity to the composition of the expert panel, which the validation plan mitigates but cannot eliminate. The normalisation strategy assumes that validated action thresholds exist for each instrument, which is truer for the biomechanical domain than for the environmental one. Finally, the matched-plant design, chosen for feasibility, cannot exclude residual plant-level confounding as fully as individual randomisation would.

## 6. Conclusion

Manual loading and unloading imposes a multi-dimensional load that the prevailing single-domain instruments, and even the recent MCDM frameworks built upon them, characterise only partially. This paper has set out the Integrated Human-factor and Ergonomic-load assessment Framework as a response: a five-layer architecture that fuses biomechanical, physiological, cognitive, and environmental exposure into a single auditable Composite Risk Index, triangulates the classical load-limit criteria, and embeds the result in a control-selection and continual-improvement cycle. The scientific contribution is to unify the MCDM-weighting and multi-domain-index traditions for the loading and unloading task for the first time; the practical contribution is a transparent basis for prioritising interventions across competing hazards. The framework's central claims remain hypotheses, and the accompanying matched-plant protocol is offered so that they can be tested rather than asserted. Future work should execute that validation, refine the domain weights against injury data, and exploit emerging wearable and vision-based sensing to automate multi-domain acquisition, moving the framework from proposal to routine industrial practice.

## Abbreviations

| | |
|---|---|
| AHP | Analytic Hierarchy Process |
| ICC | Intraclass Correlation Coefficient |
| IHEF | Integrated Human-factor and Ergonomic-Load Assessment Framework |
| KPI | Key Performance Indicator |
| LI | Lifting Index |
| LTI | Lost-Time Injury |
| MCDM | Multi-Criteria Decision-Making |
| NASA-TLX | National Aeronautics and Space Administration Task Load Index |
| NIOSH | National Institute for Occupational Safety and Health |
| PDCA | Plan-Do-Check-Act |
| REBA | Rapid Entire Body Assessment |
| RLE | Revised Lifting Equation |
| RULA | Rapid Upper Limb Assessment |
| WBGT | Wet-Bulb Globe Temperature |
| WMSD | Work-related Musculoskeletal Disorder |

## Author Contributions

**Akhmadbek Jalilov:** Conceptualization, Investigation, Methodology, Writing – original draft

**Narziev Shovkiddin Murtozaevich:** Methodology, Validation, Writing – review & editing

## Conflicts of Interest

The authors declare no conflicts of interest.

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