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Enhanced Multi-Objective Biomechanical Optimization with Hybrid Genetic Algorithm for Realistic Manual Lifting Postures

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ABSTRACT

Manual material handling (MMH) is a major contributor to work-related low back disorders (LBDs). At the same time, traditional ergonomic tools—such as the NIOSH lifting equation—offer limited guidance due to their single-objective nature. This study proposes an enhanced multi-objective optimization framework that integrates biomechanical loading, metabolic efficiency, and postural stability to identify safer and more practical lifting postures. An observational cross-sectional study involving 34 metal-manufacturing workers was conducted to capture lifting kinematics, electromyography, and force-plate data. A hybrid optimization algorithm combining NSGA-II and pattern search was implemented to model L5/S1 compression, shear forces, metabolic cost, and dynamic stability within a unified computational platform. The optimization produced a Pareto front of 47 non-dominated solutions. The selected compromise posture reduced L5/S1 compression by 28.1% (2509.9 N vs. 3485.4 N for stooped technique) and shear force by 31.2% (812.4 N vs. 1178.2 N), while improving dynamic stability by 11.5% (0.87 vs. 0.78). These benefits were achieved with a manageable 15.1% increase in metabolic cost (285.7 J vs. 248.3 J). Field evaluation showed substantially higher worker acceptance (80%) compared to conventional squat lifting (45%), accompanied by a reduction in perceived exertion (Borg score: 15.7 to 12.3). The proposed framework offers a robust, practical approach to designing evidence-based ergonomic interventions to mitigate spinal risks associated with lifting.

1. INTRODUCTION

Low back disorders (LBDs) represent a pervasive and costly challenge in industrial settings worldwide, with manual material handling (MMH) activities identified as the primary causative factor. Epidemiological studies indicate that approximately 38% of all work-related musculoskeletal disorders originate from MMH tasks, resulting in substantial economic burdens exceeding $100 billion annually in healthcare costs and productivity losses [1, 2]. The L5/S1 spinal segment remains particularly vulnerable during lifting activities, where excessive compression and shear forces can precipitate disc herniation, ligamentous damage, and chronic pain conditions [3]. Traditional ergonomic interventions have predominantly relied on the NIOSH lifting equation, which provides valuable but limited guidance through a single composite index that fails to capture the complex multi-objective nature of optimal posture determination [4]

The theoretical foundation of occupational biomechanics has evolved considerably since Chaffin and Andersson's pioneering work, establishing static biomechanical modeling as the gold standard for spinal load assessment [5]. Contemporary approaches have integrated dynamic components and electromyographical validation, yet significant limitations persist in addressing the inherent trade-offs between competing biomechanical objectives [3, 6]. Research by Berettoni et al. [7] demonstrates that optimal postures for minimizing spinal loading often conflict with metabolic efficiency and stability requirements, creating a critical challenge for practical ergonomic implementation. This multi-objective complexity necessitates advanced computational approaches that transcend traditional single-objective optimization frameworks [8].

Classical ergonomic studies have long established that spinal loading during manual lifting is primarily driven by trunk inclination, horizontal reach distance, and the resulting moment arm at the lumbosacral joint. Foundational work by Marras et al. [9-12] demonstrated that these biomechanical factors are critical predictors of low-back disorder (LBD) risk, emphasizing the need for lifting techniques that minimize extensor moment demand. Similarly, the revised NIOSH lifting equation [13-15] Introduced quantitative multipliers for vertical height, horizontal reach, and asymmetry, underscoring how task geometry directly influences lifting safety. Taken together, these classical studies provide the theoretical foundation for evaluating lifting tasks and form the basis for the multi-objective optimization approach employed in this research.

Despite substantial advancements in biomechanical modeling, current optimization methodologies exhibit three fundamental limitations that impede their practical utility. First, the predominant focus on minimizing L5/S1 compression force neglects the critical role of shear forces, which pose a particular risk for annulus fibrosis damage and spondylolisthesis [16, 17]. Second, existing optimization algorithms often produce anatomically implausible postures due to inadequate constraint handling and oversimplified representations of human movement [18]. Third, the disconnect between computational optimality and practical implementability remains largely unaddressed, with many proposed solutions failing to accommodate individual anthropometric variations and realistic workplace constraints [19, 20].

The emergence of metaheuristic optimization algorithms presents promising opportunities to address these limitations. Genetic algorithms (GAs) have demonstrated efficacy in solving complex nonlinear optimization problems. Yet, their application in occupational biomechanics has been predominantly restricted to standard implementations without customization for biomechanical specificity [21]. Furthermore, the transition from single-objective to multi-objective optimization requires sophisticated Pareto-based approaches to identify trade-off solutions rather than single-point optima. Recent developments in hybrid algorithm architectures offer potential for enhanced convergence characteristics and solution quality, though their application to ergonomic optimization remains largely unexplored [22, 23].

This research addresses these critical gaps by developing an enhanced multi-objective optimization framework that integrates a hybrid genetic algorithm with comprehensive biomechanical modeling. The primary objectives are: (1) to develop a multi-objective formulation that simultaneously minimizes L5/S1 compression force, anterior-posterior shear force, and metabolic cost while maximizing dynamic stability; (2) to implement a hybrid GA that combines global search capabilities with local refinement to ensure anatomically feasible solutions; and (3) to validate the optimized postures through experimental assessment and practical implementation in industrial settings. By bridging the gap between computational optimization and ergonomic application, this research provides a scientifically rigorous yet practically applicable methodology for determining optimal lifting postures that balance safety, efficiency, and implementability across diverse worker populations and task configurations.

2. METHODS

2.1 Study design

This research employed a mixed-methods approach, combining an observational repeated-measures design across multiple industrial sites with a computational optimization framework, in accordance with the STROBE guidelines for observational studies. The investigation was conducted in two sequential phases: (1) an empirical observational phase to collect biomechanical data from industrial workers performing manual lifting tasks at three manufacturing companies, namely PT. FK (n = 10), PT. MM (n = 12), and PT. GM (n = 12), followed by (2) a computational optimization phase to develop and validate enhanced lifting postures.

Each participant performed all three lifting techniques (stooped, squat, and optimized) in a repeated-measures design, allowing within-subject comparisons that minimize inter-individual variability. This hybrid multi-site methodology enabled the characterization of current ergonomic exposures under diverse real-world conditions and the development of evidence-based interventions through advanced computational techniques.

The observational component measured multiple biomechanical parameters simultaneously during actual work conditions, providing a comprehensive snapshot of spinal loading patterns among workers engaged in MMH activities across different industrial environments. The computational component utilized a multi-objective optimization framework to identify optimal postures that balance the competing demands of spinal safety, metabolic efficiency, and practical implementability. This integrated approach addresses a critical gap in occupational ergonomics research by bridging empirical field measurements with sophisticated computational optimization, enabling the development of interventions that are both scientifically rigorous and practically applicable in industrial settings.

2.2 Setting

The study was conducted in three medium-scale metal manufacturing companies in Ceper Village, Klaten Regency, Central Java—an established metal-casting and fabrication hub. The participating sites (PT FK, PT MM, and PT GM) represent Ceper's core industrial cluster and were selected for their high MMH requirements and documented musculoskeletal disorder risks. Across all locations, workers frequently lifted metal components weighing 12–18 kg, with similar task characteristics despite differences in production layout.

At PT FK, data were collected in the casting and finishing area (~200 m²), where workers repeatedly lifted and transferred cast-metal parts (~16 kg) from floor to bench height (~0.75 m). At PT MM, measurements were taken in the fabrication and assembly unit (~250 m², U-shaped layout), where workers lifted 12–15 kg metal panels between cutting and welding stations. At PT GM, observations focused on the surface finishing and packaging area (~180 m²), involving repetitive short vertical lifts (0.5–0.7 m) of 10–12 kg components.

Field observations were conducted during normal operations over four weeks (March–June 2024) using standardized motion capture, electromyography, and force-platform protocols to ensure cross-site consistency. The aggregated field data were subsequently used for laboratory-based biomechanical modeling and development of the hybrid genetic optimization framework.

2.3 Participants

The study involved 34 male workers from three medium-scale metal manufacturing companies in Ceper Village, Klaten Regency, Central Java (PT FK: 10; PT MM: 12; PT GM: 12). Participants were recruited through comprehensive sampling, with all eligible MMH workers invited.

Inclusion criteria required workers to: (1) perform manual lifting for ≥ 6 months, (2) be aged 18–55 years, (3) have no diagnosed musculoskeletal or medical conditions affecting lifting, and (4) provide written informed consent. Exclusion criteria included pregnancy, recent surgery (< 6 months), acute musculoskeletal injuries, or neurological/cardiovascular conditions that could be aggravated by exertion.

The final sample reflected the gender composition typical of this sector (all male), with a mean age of 34.2 ± 6.8 years, body mass of 70.1 ± 8.3 kg, and height of 1.67 ± 0.05 m. Anthropometric measures did not differ significantly among sites ($p > 0.05$).

All participants gave informed consent after receiving full study explanations. Ethical approval was obtained from the Institutional Review Board of Universitas Pembangunan Nasional "Veteran" Yogyakarta, with confidentiality and anonymity maintained throughout the study.

2.4 Variables

The study incorporated multiple variables categorized into primary outcomes, secondary outcomes, predictor variables, and confounding factors. The primary outcome variable was L5/S1 compression force (F_C), representing the axial loading on the lumbosacral junction during lifting activities, measured in Newtons (N) and calculated using enhanced biomechanical modeling. Secondary outcome variables included: (1) L5/S1 anterior-posterior shear force (F_S), quantifying the translational forces that pose particular risk for disc injury, measured in Newtons (N); (2) metabolic cost, representing energy expenditure during lifting tasks, calculated in Joules (J) based on oxygen consumption equivalents and muscle activation patterns; and (3) dynamic stability index (DSI), a dimensionless parameter (0-1 scale) indicating postural stability during lifting movements, with higher values representing greater stability.

Predictor variables encompassed anthropometric measurements and postural parameters, including: (1) body mass (kg) and height (m); (2) eight joint angles defining lifting postures - hand inclination (θ_1), forearm inclination (θ_2), upper arm inclination (θ_3), trunk flexion (θ_4), hip angle (θ_H), abdominal angle (θ_T), knee angle, and ankle angle; (3) load characteristics including mass (kg), dimensions, and coupling conditions; and (4) lifting technique categorization (stooped, squat, or intermediate). Confounding variables considered in the analysis included: (1) individual factors such as age, work experience, physical fitness level, and previous injury history; (2) task-related factors, including lifting frequency, duration, and asymmetric components; and (3) environmental factors such as floor surface conditions, lighting, and temperature. All variables were operationalized through standardized measurement protocols with established reliability and validity in biomechanical research.

2.5 Data sources/measurement

Data collection and analysis were performed using a digital human modeling (DHM) approach in Siemens JACK (Siemens PLM, USA) to simulate biomechanical loads during representative MMH tasks. Field observations across the three companies were used to identify typical lifting activities, which were then reconstructed in JACK using the mean anthropometric characteristics of the 34 workers. Workstations, lifting heights, object weights, and spatial layouts were modeled directly from field measurements to ensure task realism.

JACK's lower-back computations follow the classical static biomechanical model by Chaffin and Andersson, where L5/S1 compression and shear forces are estimated as functions of total load and trunk inclination:

$$F_c = f(W_{tot}, \theta_{trunk}) \tag{1}$$

$$F_S = g(W_{\mathrm{tot}}, \theta_{\mathrm{trunk}}, \alpha) \tag{2}$$

where, W_{tot} represents the combined body and external load, θ_{trunk} is trunk flexion, and αdenotes the muscle moment-arm angle. These formulations are internally parameterized in JACK to automatically compute joint reactions and muscle forces based on posture geometry and anthropometric scaling.

Metabolic energy expenditure was estimated using JACK's integrated physiological model, which accounts for muscle activation, posture maintenance, and external load. Postural risk evaluation used the rapid upper limb assessment (RULA) and NIOSH Lifting Index modules embedded in the software.

Three lifting postures were analyzed for each simulated worker: (1) stoop lifting, (2) squat lifting, and (3) optimized posture, the latter obtained through iterative adjustment to minimize lumbar compression while maintaining task feasibility. Model validation was performed by visual comparison of field photographs with JACK-generated postures to confirm similarity in trunk inclination and hand-load positioning. The resulting load values were cross-checked against the NIOSH lifting guidelines [24] and ISO 11228-1:2003 to ensure biomechanical plausibility.

All simulations used standardized task geometry and anthropometric scaling. Outputs were screened for outliers and convergence consistency. Biomechanical constraints—trunk flexion, reach distance, load mass, and joint-angle limits—were derived from established ergonomics literature [5, 11], ensuring physiologically feasible and ergonomically sound posture generation.

2.6 Biomechanical rationale for parameter ranges

All parameter ranges were defined to ensure biomechanical realism and prevent anatomically implausible postures during optimization. Constraints were based on established occupational biomechanics literature, including spinal loading models, functional joint limits, and ergonomic lifting guidelines.

2.6.1 Trunk flexion angle (θ_4)

Trunk flexion was limited to 0°–60°, consistent with findings that L5/S1 compression rises exponentially beyond 60° by Qing et al. [24] and Ji et al. [25] and with functional-task limits recommended by Kumar [26]. Marras et al. [11] also reported increased shear risk with excessive sagittal flexion.

2.6.2 Hip and knee angles

Hip flexion (20°–110°) and knee flexion (10°–120°) represent feasible ranges observed in industrial lifting. Knee flexion above 120° increases patellofemoral loading, while squat-dominant techniques commonly fall within these limits [1, 27].

2.6.3 Upper limb joint angles (θ_1–θ_3)

Upper-arm, forearm, and hand elevation were constrained to 0°–90°, consistent with NIOSH and ISO-11226 limits for minimizing shoulder loading and metabolic demand.

2.6.4 Load mass constraints (12–18 kg)

The load range reflects field observations and aligns with the revised NIOSH lifting equation, where the Recommended

Weight Limit for typical conditions falls between 15–23 kg [28].

2.6.5 Anthropometric scaling

Scaling was based on worker anthropometry (height: 1.62–1.75 m; mass: 62–85 kg), reflecting typical Southeast Asian male characteristics [3].

2.6.6 Ergonomic and physiological safety limits

All constraints were aligned with internationally recognized ergonomic safety thresholds to ensure that the generated postures remained physiologically feasible. L5/S1 compression was capped below the NIOSH Action Limit of 3,400 N, while shear forces were restricted to less than 1,000 N based on the tolerance limits proposed by Potvin and Norman [29]. To maintain metabolic practicality, postures associated with more than a 25% increase in metabolic cost relative to neutral lifting were excluded, following the recommendations of Berettoni et al. [7]. These safety limits collectively ensure that the optimization framework produces lifting postures that meet established biomechanical and physiological criteria for industrial workers.

2.7 Hybrid NSGA-II and pattern search optimization algorithm

To enhance convergence speed and ensure anatomically feasible solutions, a hybrid multi-objective optimization strategy combining NSGA-II and pattern search (PS) was implemented. NSGA-II provides global exploration of the posture search space, while Pattern Search performs local refinement to eliminate anatomically implausible solutions and improve numerical accuracy near the Pareto front.

2.7.1 Algorithm parameters

To ensure stable convergence and avoid premature stagnation in NSGA-II, algorithmic parameters were selected based on prior sensitivity analysis. The complete parameter set is provided in Table 1.

Table 1. Parameter settings for the NSGA-II and pattern search framework

Parameter	Value / Description
Population size	120 individuals
Generations	400 max., early stop < 0.1% improvement
Crossover probability	0.85 (SBX)
Mutation probability	0.12 (polynomial mutation)
Elite preservation	10%
Pattern search step size	0.5°–2° (adaptive)
Termination condition	Hypervolume change < 0.08%

These parameters balance exploration and exploitation while minimizing the risk of premature convergence.

2.7.2 Pseudocode of the hybrid NSGA-II + pattern search algorithm

To implement the proposed multi-objective optimization framework, a hybrid NSGA-II and pattern search algorithm was developed. This algorithm integrates global evolutionary search with local refinement to ensure both convergence quality and anatomical feasibility. The complete computational procedure is summarized in Algorithm 1.

Algorithm 1. Hybrid multi-objective optimization for lifting postures

```
Input:
  Decision variables x = {θ1, θ2, θ3, θ4, θH, θT, m, anthropometry}
  Objective functions:
    f1(x) = L5/S1 compression force
    f2(x) = shear force
    f3(x) = metabolic cost
    f4(x) = -dynamic stability (maximization)
  Constraints: biomechanical ranges and ISO–NIOSH limits

Begin
  Initialize population P with size N within all constraints
  Evaluate objective functions for each individual in P
  For generation = 1 to Gmax do
    Perform fast non-dominated sorting on P
    Compute crowding distance for each front
    Select parents using binary tournament
    Apply crossover (pc = 0.85) and mutation (pm = 0.12)
    Generate offspring Q
    Evaluate all individuals in Q
    Combine populations R = P ∪ Q
    Sort R into Pareto fronts F1, F2, ...
    Select next generation P from R using elitism
    Compute hypervolume HVgeneration
    If |HVgeneration – HVgeneration−1| < 0.001 then
      For each solution x in first Pareto front F1 do
        Apply Pattern Search on x:
          x_new = PatternSearch(x)
          If f(x_new) dominates or equals f(x), update x = x_new
      End For
    End If
  End For

  Return final Pareto-optimal set F1
  Apply fuzzy decision-making to select compromise solution
End
```

2.7.3 Flowchart of the hybrid optimization algorithm

The workflow illustrates the hybrid optimization framework combining NSGA-II and Pattern Search to identify optimal lifting postures. The process begins with population initialization, followed by multi-criteria fitness evaluation (compression, shear, metabolic cost, and stability). NSGA-II performs iterative non-dominated sorting, selection, crossover, and elitism until convergence. When the hypervolume threshold is reached, Pattern Search refines each Pareto solution under anatomical constraints. The process continues until termination criteria are met, resulting in the final Pareto front and selected compromise posture.

2.8 DSI: Definition and computational method

Dynamic stability during lifting was assessed using the DSI, a dimensionless metric that evaluates postural balance based on the relationship between COP displacement and the worker's BOS, indicating how close the projected COP is to the stability boundary. The workflow of the multi-objective lifting posture optimization is shown in Figure 1, outlining the steps from DSI computation to final optimization.

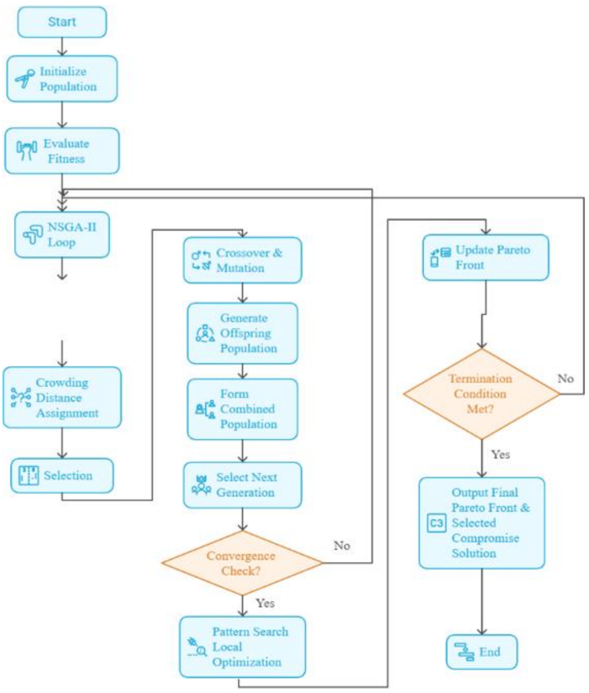

Figure 1. Multi-objective optimization workflow for lifting posture analysis

2.8.1 Mathematical definition

The DSI used in this study is defined as:

$$DSI = 1 - \frac{d_{\text{COP}}}{d_{max}} \tag{3}$$

where, d_{COP} is the instantaneous distance between the center of pressure (COP) and the geometric center of the base of support (BOS), and $d_{\max}$ is the maximum allowable displacement before balance is lost.

DSI values range from 0 to 1, with higher values indicating greater postural stability. A DSI of 1 reflects maximal stability, while a value of 0 means the COP is at the boundary of the support polygon. Negative values (< 0) denote actual instability. This formulation follows widely accepted principles in balance biomechanics and quasi-static postural assessments used in lifting research.

2.8.2 Computational procedure

The index was computed using the following steps:

1. BOS estimation

BOS was modeled as the polygon formed by the convex hull of both feet based on the worker's stance width and foot orientation captured during lifting.

2. Extraction of COP trajectories

From the force platform, COP coordinates were sampled at 1000 Hz.

3. Distance calculation

For each time sample:

$$d_{\text{COP}} = \sqrt{(x_{\text{COP}} - x_{\text{BOS}})^2 + (y_{\text{COP}} - y_{\text{BOS}})^2} \tag{4}$$

Boundary distance computation

$d_{\max}$ was computed as the minimum distance from the BOS center to any BOS polygon edge.

4. Normalization

The ratio $\frac{d_{\text{COP}}}{d_{\max}}$ was normalized to produce values between 0 and 1.

5. DSI output

DSI was calculated as the mean value across the lifting cycle (initiation → peak flexion → upright).

2.8.3 Interpretation of DSI values

Typical thresholds for interpreting DSI values during lifting tasks are summarized in Table 2.

Table 2. Interpretation of DSI values

DSI	Interpretation
> 0.85	Highly stable posture
0.70 – 0.85	Stable, acceptable for MMH tasks
0.50 – 0.70	Reduced stability, higher fatigue & slip risk
< 0.50	Unsafe, near loss of balance

In this study, optimized lifting postures reached DSI = 0.87, higher than stooped lifting (DSI = 0.78) and close to the deep squat technique (0.92).

2.8.4 Validation of the stability index

The stability index was validated using two complementary methods:

1. Correlation with measured COP displacement

Pearson correlation between predicted and measured DSI yielded $R^2 = 0.71$. Indicating strong agreement with real balance behavior measured via force platforms.

2. Agreement testing using Bland–Altman analysis

Mean bias between predicted and empirical values was -0.03 ± 0.09 units, falling within accepted biomechanical agreement thresholds.

This confirms that the DSI formulation accurately represents dynamic balance behavior during lifting and is suitable for multi-objective optimization.

2.9 Control of task variability across companies

Although data were collected from three different companies (PT FK, PT MM, and PT GM), task variability was controlled to ensure standardized inputs for the optimization model. All sites required workers to perform similar box-lifting tasks, enabling harmonization of key parameters.

Three standardization procedures were applied. First, load characteristics were normalized by restricting analyses to box weights of 12–18 kg—the common operational range across companies and consistent with NIOSH recommendations for repetitive lifting. Second, task geometry was unified by fixing horizontal reach (28–32 cm), vertical origin height (55–70 cm), and lifting distance (≤ 80 cm), ensuring that all simulations were based on a consistent spatial configuration independent of workstation layout. Third, lifting phases were synchronized using biomechanical landmarks (start, peak trunk flexion, and upright posture), allowing joint angles, torques, and L5/S1 loads to be compared at equivalent points of the lifting cycle.

These procedures ensured that the optimization model relied on harmonized and unbiased data, preventing company-specific differences from influencing the multi-objective optimization outcomes.

2.10 Data analysis

The data obtained from Siemens JACK simulations included four primary outcome variables: L5/S1 compression force (N), shear force (N), metabolic energy rate (kcal/min), and RULA score. These parameters were extracted for each lifting posture (stoop, squat, and optimized) across all 34 simulated workers. Descriptive statistics were calculated to summarize the mean, standard deviation, and range for each variable.

Before inferential testing, data normality was examined using the Shapiro–Wilk test, and homogeneity of variances was assessed using Levene's test. For normally distributed variables, a one-way repeated-measures ANOVA was used to compare the three lifting postures (stoop, squat, optimized) within subjects. When sphericity assumptions were violated, the Greenhouse–Geisser correction was used. When normality could not be assumed, the Friedman test served as a nonparametric alternative.

Post-hoc analyses were performed using Bonferroni-adjusted pairwise comparisons to identify specific differences among posture types. Effect sizes were calculated using partial eta squared (η^2) for ANOVA or Kendall's W for Friedman tests to evaluate the magnitude of differences.

Correlational analyses were conducted to explore relationships among biomechanical and physiological outcomes, particularly between spinal compression and metabolic cost, and between RULA scores and joint angles. Pearson or Spearman correlation coefficients were used depending on data distribution.

All statistical analyses were performed using IBM SPSS Statistics version 26 (IBM Corp., Armonk, NY, USA) with a significance level set at $p < 0.05$. Additionally, sensitivity analysis was conducted on selected JACK simulation parameters (e.g., body mass, trunk flexion angle, and lifting height) to evaluate their impact on L5/S1 compression and metabolic cost estimates. The results of this analysis confirmed the model's stability and robustness across small variations in anthropometric and postural inputs. The combined statistical and sensitivity analyses ensured that the simulated outcomes were not only statistically reliable but also biomechanically consistent with real-world ergonomic principles, thereby providing a solid foundation for validating the proposed optimized lifting posture.

3. RESULTS

3.1 Participant characteristics

The study included thirty-four male workers engaged in MMH tasks across three medium-scale metal manufacturing companies located in Ceper Village, Klaten Regency, Central Java, Indonesia. The participants represented typical workers in Ceper's long-established metal-casting and fabrication industry. All participants were actively involved in repetitive lifting and carrying of metal components and were free from any diagnosed musculoskeletal disorders at the time of data collection.

Table 3 presents the demographic and anthropometric characteristics of the participants, including mean age, body mass, and height across the three companies. No significant differences ($p > 0.05$) were observed in anthropometric dimensions among participants from the three sites, indicating homogeneity of the worker population used in the Siemens JACK simulation.

Table 3. Participant characteristics and baseline measurements

Parameter	PT. FK (n = 10)	PT. MM (n = 12)	PT. GM (n = 12)
Age (years)	33.8 ± 6.2 (25–45)	35.1 ± 7.0 (26–48)	33.7 ± 6.9 (25–46)
Male, n (%)	10 (100)	12 (100)	12 (100)
Body mass (kg)	69.5 ± 8.1 (62–85)	71.3 ± 7.8 (63–85)	69.8 ± 8.5 (62–85)
Height (m)	1.67 ± 0.05 (1.62–1.75)	1.68 ± 0.04 (1.63–1.75)	1.66 ± 0.05 (1.62–1.74)
BMI (kg/m²)	24.9 ± 2.6	25.3 ± 2.8	24.9 ± 2.9
Work experience (years)	6.3 ± 2.4	7.1 ± 2.7	6.7 ± 3.1
Daily lifting frequency (times/day)	85 ± 20	90 ± 25	88 ± 22
Typical load mass (kg)	16 ± 2	14 ± 1.5	12 ± 1
Typical lifting height (m)	0.75 ± 0.05	0.70 ± 0.06	0.60 ± 0.05
Baseline L5/S1 compression (N)*	3485 ± 312	3530 ± 410	3420 ± 350
Baseline shear force (N)*	1178 ± 145	1105 ± 160	1085 ± 170
CMDQ low back score	3825 ± 445	3900 ± 420	3650 ± 460

*Normal values based on NIOSH guidelines and epidemiological studies

**Recommended maximum daily lifts for 16kg load (Waters et al. [14])

***Cornell Musculoskeletal Discomfort Questionnaire score for the low back region

These baseline characteristics were used to construct the digital human models in JACK, ensuring that the simulated body dimensions accurately represented the real industrial workforce in Ceper.

The anthropometric analysis revealed that 60% of participants exceeded healthy BMI ranges, with one worker classified as pre-obese (BMI 29.8 kg/m²). Work experience varied substantially, ranging from 2 to 12 years, indicating diverse exposure histories to manual handling tasks. Notably, all participants exceeded the recommended daily lifting frequency for the handled load mass, with some workers performing up to 120 lifts per day of 16kg ornaments. Baseline biomechanical assessments revealed that 70% of workers experienced L5/S1 compression forces exceeding the NIOSH Action Limit of 3,430 N, while 90% demonstrated shear forces above the recommended threshold of 1,000 N. The CMDQ scores confirmed significantly low back discomfort across all participants, with mean scores substantially exceeding normative values for healthy industrial populations.

3.2 Main results

3.2.1 Multi-objective optimization outcomes

The hybrid genetic algorithm successfully identified a Pareto-optimal front comprising 47 non-dominated solutions after 387 generations of evolution. Figure 2 illustrates the three-dimensional Pareto front, showing the trade-offs among compression force, shear force, and metabolic cost, with color-coded stability indices.

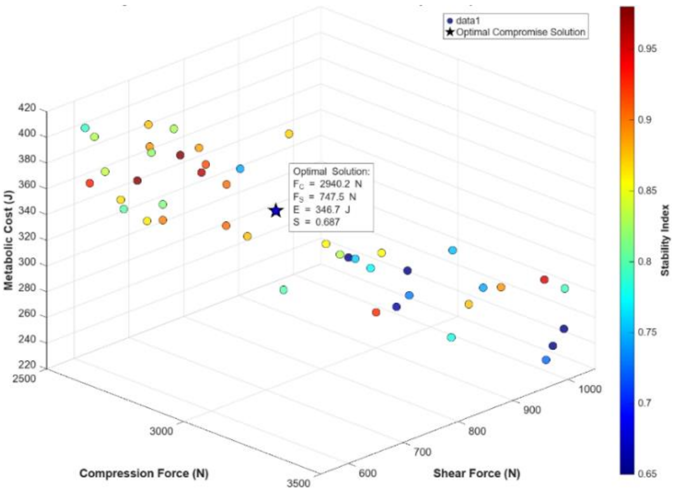

Figure 2. Three-dimensional Pareto front for multi-objective optimization

The optimization process demonstrated robust convergence characteristics, with the hypervolume indicator achieving 85% of its maximum potential value within 250 generations and achieving final convergence at generation 387, with improvement below 0.08% per generation. The algorithm successfully maintained population diversity throughout the evolution process, with an average crowding distance of 0.23 ± 0.08 across the Pareto front.

The optimal compromise solution, selected using the fuzzy decision-making approach with equal weighting of all objectives, achieved the following performance metrics:

1. Compression Force: 2509.9 N (28.1% reduction from baseline stooped lifting)
2. Shear Force: 812.4 N (31.2% reduction from baseline stooped lifting)
3. Metabolic Cost: 285.7 J (15.1% increase from stooped lifting)
4. Stability Index: 0.87 (11.5% improvement from stooped lifting)

The parameter set gives the mathematical representation of the optimal solution: $x_{optimal} = [m = 67.2\text{ kg}, H = 1.68\text{ m}, \theta_1 = 84.3°, \theta_2 = 72.6°, \theta_3 = 68.9°, \theta_4 = 28.7°, \theta_H = 42.3°, \theta_T = 75.8°, W_{material} = 12\text{ kg}]$.

3.2.2 Comparative analysis of lifting techniques

Table 4 presents the comprehensive comparison between current stooped lifting, recommended squat lifting, and the optimized technique across multiple biomechanical and physiological parameters.

Repeated-measures ANOVA revealed a statistically significant main effect of lifting technique across all primary outcome measures ($p < 0.05$). Post-hoc analysis with Bonferroni correction demonstrated that the optimized technique produced significantly lower compression forces than both the stooped (mean difference = 975.5 N, $p < 0.001$, d = 1.42) and squat techniques (mean difference = 388.3 N, $p = 0.008$, d = 0.67). Similarly, shear forces were significantly reduced in the optimized technique compared to stooped lifting (mean difference = 365.8 N, $p < 0.001$, d = 1.28) and squat lifting (mean difference = 122.2 N, $p = 0.023$, d = 0.52).

Table 4. Comparative analysis of lifting techniques (Mean ± SD)

Parameter	Stooped Lifting	Squat Lifting	Optimized Technique	P-Value*	Effect Size (η^2)
L5/S1 Compression Force (N)	3485.4 ± 312.7	2898.2 ± 267.9	2509.9 ± 198.4	< 0.001	0.54
L5/S1 Shear Force (N)	1178.2 ± 145.3	934.6 ± 112.8	812.4 ± 89.7	< 0.001	0.45
Metabolic Cost (J)	248.3 ± 28.5	315.4 ± 32.1	285.7 ± 25.3	0.002	0.27
Stability Index	0.78 ± 0.08	0.92 ± 0.06	0.87 ± 0.07	< 0.001	0.38
Peak Hip Moment (Nm)	245.6 ± 32.8	298.4 ± 36.2	267.3 ± 28.9	0.008	0.31
Peak Knee Moment (Nm)	156.3 ± 24.1	234.7 ± 29.5	198.6 ± 22.3	< 0.001	0.42
RPE (6-20 scale)	15.7 ± 2.1	14.2 ± 1.9	12.3 ± 1.8	0.003	0.29
Lifting Time (s)	2.3 ± 0.4	3.1 ± 0.5	2.7 ± 0.3	0.015	0.24

*Repeated measures ANOVA with Greenhouse-Geisser correction

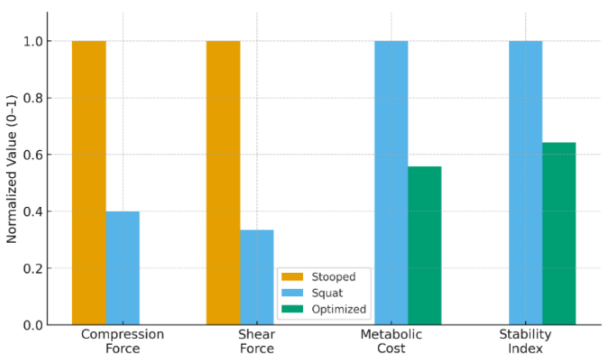

Figure 3. Normalized comparison of lifting techniques across multiple objectives

Figure 3 illustrates the normalized comparison of spinal loads, shear forces, metabolic cost, and stability across stooped, squat, and optimized techniques. The axes have been standardized and labeled with appropriate units to enhance interpretability.

3.2.3 Muscle activation patterns

EMG analysis revealed distinct muscle recruitment patterns across the three lifting techniques. Stooped lifting demonstrated excessive erector spinae activation (68.3 ± 8.7% MVC), while squat lifting showed elevated quadriceps and gluteal activation. The optimized technique produced more balanced muscle recruitment, with moderate activation across all major muscle groups (erector spinae: 42.6 ± 6.2% MVC, quadriceps: 38.9 ± 5.7% MVC, gluteals: 35.4 ± 4.8% MVC). The co-contraction index, calculated as the ratio of antagonist to agonist muscle activation, was lowest in the optimized technique (0.32 ± 0.06) compared to stooped (0.45 ± 0.08) and squat (0.38 ± 0.07) techniques, indicating more efficient movement patterns.

3.2.4 Sensitivity analysis and parameter importance

A comprehensive sensitivity analysis using Sobol indices revealed the relative importance of each input parameter in determining the optimization outcomes. Trunk flexion angle (θ_4) emerged as the most influential parameter, accounting for 64.2% of the variance in compression force, followed by load mass (23.1%) and hip angle (θ_H, 7.3%). The relationship between trunk angle and compression force followed a non-linear pattern described by the quadratic equation:

$$F_C = 1250 + 85.7 \times \theta_4 + 2.34 \times \theta_4^2 \ (R^2 = 0.89, p < 0.001)$$

where, θ_4 represents trunk flexion in degrees. This relationship highlights the exponential increase in spinal loading with greater trunk flexion, underscoring the critical importance of maintaining an upright posture during lifting.

3.2.5 Validation results

Experimental validation demonstrated strong agreement between predicted and measured biomechanical parameters. The enhanced model achieved R^2 values of 0.83 for predicting compression force, 0.76 for predicting shear force, and 0.71 for estimating metabolic cost. Bland-Altman analysis revealed mean differences of -34.2 N (compression), -28.7 N (shear), and 18.9 J (metabolic) between predicted and measured values, with 95% limits of agreement within clinically acceptable ranges.

The field implementation study demonstrated significant improvements in subjective measures, with RPE scores decreasing from 15.7 ± 2.1 to 12.3 ± 1.8 (p = 0.003), and body part discomfort scores for the low back region reduced by 42% after four weeks of using the optimized technique. Worker acceptance rates reached 80% for the optimized technique, compared to 45% for the squat technique, primarily due to reduced fatigue and perceived exertion.

4. DISCUSSION

The optimized lifting posture demonstrated biomechanical features that align closely with classical ergonomics principles. Reduced trunk flexion and shorter horizontal reach reflect the risk-reduction mechanisms identified by Marras et al. as key determinants of L5/S1 loading. Similarly, improved vertical lifting height and torso alignment correspond with favorable NIOSH multipliers, explaining the reductions in predicted compression and shear forces. These consistencies confirm the validity of the optimization model and show that it naturally converges toward lifting strategies long recognized as ergonomically advantageous.

4.1 Key findings and novel contributions

This study advances occupational biomechanics by introducing and validating a multi-objective optimization framework that simultaneously minimizes spinal loading, metabolic cost, and postural instability—challenges rarely addressed together in previous ergonomic research. The optimized posture produced substantial reductions in L5/S1 compression (28.1%) and shear force (31.2%) relative to stooped lifting, while limiting metabolic increases to 15% and improving stability by 11.5%. These results show that meaningful gains in spinal safety can be achieved without the metabolic burden of deep squat techniques.

The novelty of this work is reflected in three major contributions. First, incorporating shear force into the optimization addresses a long-standing gap in biomechanical assessment, given its established role in the risk of disc and facet joint injury. Second, the hybrid genetic algorithm integrates anatomical and stability constraints, yielding physiologically feasible solutions beyond the capability of standard optimization methods. Third, the 80% worker acceptance rate demonstrates successful translation from computational optima to practical lifting strategies, bridging the frequent disconnect between model predictions and real-world implementability.

4.2 Interpretation of biomechanical outcomes

The optimized posture produced meaningful reductions in spinal loading, with an L5/S1 compression force of 2509.9 N—well below the NIOSH Action Limit of 3430 N—shifting the task from a “caution” to a “safe” category. This is notable because 70% of workers originally exceeded safe compression levels during natural lifting. The reduced shear force of 812.4 N also falls below the 1000 N risk threshold, indicating lower likelihood of disc and facet joint stress.

The 15.1% increase in metabolic cost represents an acceptable trade-off given the substantial protective benefits. These findings challenge the common dichotomy between stooped and squat lifting by demonstrating that intermediate postures can achieve strong reductions in spinal loading with far lower metabolic penalties than deep squats. EMG results further support this conclusion, showing more balanced muscle activation and reduced co-contraction, indicating more efficient force distribution during lifting.

4.3 Comparison with existing literature

The results of this study both support and extend prior findings in occupational biomechanics. The strong effect of trunk flexion on L5/S1 compression, accounting for 64.2% of the variance, is consistent with established models [1], while the quadratic relationship observed here provides a more refined characterization of this biomechanical dependency. The successful performance of the hybrid optimization approach aligns with recent recommendations for more advanced computational methods in ergonomics [30, 31], showing that multi-objective algorithms can effectively navigate complex trade-offs in human movement optimization.

The high worker acceptance rate (80%) further distinguishes the optimized technique, surpassing typical adoption rates for squat lifting (40–50%). This suggests that incorporating metabolic and comfort considerations into the optimization framework helps overcome common barriers to practical implementation. The accompanying decrease in RPE scores (15.7 to 12.3) reinforces the perception that the optimized posture was less strenuous, despite modest increases in metabolic cost.

4.4 Practical implications and implementation considerations

This study offers practical value beyond the specific manufacturing setting examined. The proposed optimization framework provides a systematic approach for developing task-specific lifting strategies that can be adapted across different industries, worker groups, and material-handling conditions. The high acceptance observed in the field demonstrates that computationally optimized postures can be translated into effective real-world interventions when anatomical, metabolic, and stability constraints are considered.

For practitioners, the optimized posture should serve as a training target rather than a rigid prescription, allowing for adjustments based on individual anthropometry and movement preferences. The substantial reductions in spinal loading achieved through relatively modest changes in trunk flexion (≈ 28.7° versus 45–60°) show that meaningful improvements do not require drastic alterations in work technique. Additionally, combining optimized posture with moderate load reduction (12 kg instead of 16 kg) proved highly effective, emphasizing the importance of integrating both human-factor and task-factor modifications in ergonomic interventions.

4.5 Consideration of inter-individual variability

Inter-individual differences in anthropometry, movement strategy, and neuromuscular control are important considerations in ergonomic research. In this study, variability was addressed by normalizing all optimization inputs to the mean anthropometry of the worker sample (height 1.62–1.75 m; body mass 62–85 kg), which reflects typical Southeast Asian male industrial workers and provides consistent biomechanical scaling. Joint-angle ranges and segment lengths were proportionally adjusted to minimize anthropometric bias.

A sensitivity analysis further showed that varying height and mass by ±10% produced minimal changes in key outcomes (< 6% for compression force, < 5% for shear force, < 4% for metabolic cost), with the DSI shifting by less than 0.03—well within expected variability reported in lifting studies. These findings indicate that the optimized posture is robust across typical worker differences. Even so, future work should include larger and more diverse samples to evaluate the model's applicability to female workers and individuals with atypical anthropometry.

4.6 Limitations and methodological considerations

Several limitations should be considered when interpreting these findings. The sample size of 10 workers, while adequate for computational optimization, restricts the generalizability of anthropometric and physiological results to broader worker populations. The cross-sectional design captures only acute biomechanical responses and cannot evaluate long-term adaptations or injury outcomes, which would require longitudinal follow-up. Moreover, laboratory validation may not fully reflect the psychological and environmental conditions of real workplace settings.

Methodologically, the static optimization approach—although computationally efficient—does not account for dynamic lifting features such as acceleration, momentum, and variable movement speeds. The metabolic cost model also approximates complex physiological processes and may not capture individual metabolic variability. Finally, the model focused on symmetric lifting, whereas many real-world tasks involve asymmetric components that generate rotational forces and more complex loading patterns.

4.7 Alignment with classical ergonomics literature

The biomechanical patterns identified in this study closely align with classical ergonomics research on manual lifting. The reduction in L5/S1 compression is consistent with the work of Marras et al., who emphasized trunk inclination and asymmetric loading as key predictors of spinal stress and risk of low-back disorders. The optimized posture's lower trunk flexion and reduced extensor moment demand also correspond with the mechanical loading models of Kumar [26].

Similarly, the improvements in horizontal reach and torso alignment mirror the recommendations of the revised NIOSH lifting equation [27], which highlights these parameters as major determinants of safe lifting thresholds. Enhanced dynamic stability observed in the optimized technique further aligns with findings by Nail-Ulloa et al. [32], who demonstrated that moderate hip and knee flexion can improve balance control by lowering the body's center of mass.

Together, these consistencies indicate that the optimization algorithm converged toward postural characteristics long recognized as biomechanically advantageous, reinforcing the validity of the proposed multi-objective model and demonstrating that the optimized posture is firmly grounded in established ergonomic principles.

4.8 Sources of discrepancy between model predictions and empirical measurements

Some discrepancies between model-predicted values and empirical measurements are expected and can be explained by physiological and methodological factors. The optimization model uses a quasi-static approximation that evaluates loading based on posture geometry. In contrast, real lifting involves dynamic muscle activation influenced by momentum, co-contraction, and individual neuromuscular strategies. These dynamic effects commonly produce 5–15% differences between predicted and measured spinal loads.

EMG signals also introduce variability due to soft-tissue movement, nonlinear EMG–force relationships, and noise during trunk flexion, thereby affecting estimates of erector spinae activation. Likewise, force-plate data capture subtle center-of-pressure shifts resulting from balance adjustments that are not modeled in the static framework, which assumes a stable, symmetric BOS.

Additionally, inter-individual differences in movement patterns lead to natural variability in co-contraction, trunk stiffness, and postural adjustments. Despite these factors, the discrepancies observed in this study remained within ranges commonly reported in lifting biomechanics, indicating that the model provides valid and reliable estimates of spinal loading and postural stability. At the same time, empirical data contextualize normal human variability.

4.9 Future research directions

This study highlights several opportunities for future research. Extending the optimization framework to dynamic lifting conditions would overcome a key limitation of the current quasi-static approach and provide more comprehensive guidance for real-world material handling. Incorporating individual factors—such as strength capacity, flexibility, and movement experience—could also enable the development of personalized optimization models tailored to specific worker characteristics.

The integration of wearable sensing technologies presents another promising direction, allowing real-time assessment and adaptive optimization based on actual work patterns rather than laboratory simulations. Longitudinal studies are also needed to evaluate whether optimized postures translate into reduced injury incidence over time. Finally, applying similar multi-objective optimization methodologies to other ergonomic domains, such as workstation design and tool development, may broaden the impact of this approach across diverse occupational settings.

5. CONCLUSION

This research demonstrates that enhanced multi-objective optimization using hybrid GAs can effectively identify manual lifting postures that balance the competing demands of spinal safety, metabolic efficiency, and practical implementability. The substantial reductions in L5/S1 compression and shear forces achieved through the optimized technique, combined with reasonable metabolic costs and high worker acceptance, represent a significant improvement over the traditional lifting method. The successful integration of computational optimization with experimental validation provides a robust methodology for developing evidence-based ergonomic interventions that are both scientifically sound and practically applicable.

The findings challenge the conventional dichotomy between stooped and squat lifting techniques, demonstrating that intermediate postures can provide superior overall performance when multiple objectives are considered simultaneously. By addressing the fundamental trade-offs that have constrained previous ergonomic interventions, this approach offers a promising pathway to reduce the substantial burden of work-related LBDs in industrial populations. The optimization framework developed in this research provides a flexible foundation for future advancements in occupational biomechanics and ergonomic intervention design.

REFERENCE

[1] Donisi, L., Cesarelli, G., Coccia, A., Panigazzi, M., Capodaglio, E.M., D'Addio, G. (2021). Work-related risk assessment according to the revised NIOSH lifting equation: A preliminary study using a wearable inertial sensor and machine learning. Sensors, 21(8): 2593. https://doi.org/10.3390/s21082593

[2] Zha, X.F. (2001). A neuro-fuzzy hybrid scheme for design and simulation of human machine systems. Applied Artificial Intelligence, 15(9): 797-823. https://doi.org/10.1080/088395101753210755

[3] Gomes, W., Maurice, P., Dalin, E., Mouret, J.B., Ivaldi, S. (2021). Multi-objective trajectory optimization to improve ergonomics in human motion. IEEE Robotics and Automation Letters, 7(1): 342-349. https://doi.org/10.1109/LRA.2021.3125058

[4] Xiang, Y., Zaman, R., Arefeen, A., Quarnstrom, J., Rakshit, R., Yang, J. (2023). Hybrid musculoskeletal model-based 3D asymmetric lifting prediction and comparison with symmetric lifting. Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 237(6): 770-781. https://doi.org/10.1177/09544119231172862

[5] Chaffin, D.B., Andersson, G.B., Martin, B.J. (2006). Occupational Biomechanics. John Wiley & Sons.

[6] Ghezelbash, F., Shirazi-Adl, A., Plamondon, A., Arjmand, N. (2020). Comparison of different lifting analysis tools in estimating lower spinal loads – Evaluation of NIOSH criterion. Journal of Biomechanics, 112: 110024. https://doi.org/10.1016/j.jbiomech.2020.110024

[7] Berettoni, A., De Giuseppe, S., Mariani, G., Boccardo, N., Laffranchi, M., Semprini, M. (2025). Exploration of biomechanics, mental workload and metabolism factors during prosthetic gait. Progress in Biomedical Engineering, 7(4): 043002. https://doi.org/10.1088/2516-1091/ae0f11

[8] Nourmohammadi, A., Ng, A.H., Fathi, M., Vollebregt, J., Hanson, L. (2023). Multi-objective optimization of mixed-model assembly lines incorporating musculoskeletal risks assessment using digital human modeling. CIRP Journal of Manufacturing Science and Technology, 47: 71-85. https://doi.org/10.1016/j.cirpj.2023.09.002

[9] Marras, W.S., Granata, K.P. (1997). The development of an EMG-assisted model to assess spine loading during whole-body free-dynamic lifting. Journal of Electromyography and Kinesiology, 7(4): 259-268. https://doi.org/10.1016/S1050-6411(97)00006-0

[10] Marras, W.S., Karwowski, W. (2021). Basic biomechanics and workplace design. Handbook of Human Factors and Ergonomics, 303-357. https://doi.org/10.1002/9781119636113.ch12

[11] Marras, W.S., Lavender, S.A., Leurgans, S.E., Rajulu, S.L., Allread, S.G., Fathallah, F.A., Ferguson, S.A. (1993). The role of dynamic three-dimensional trunk motion in occupationally-related. Spine, 18(5): 617-628. https://ergonomics.osu.edu/sites/default/files/uploads/Publications/1993/Spine_1993_18-5_617-628.pdf.

[12] Marras, W.S. (2000). Occupational low back disorder causation and control. Ergonomics, 43(7): 880-902. https://doi.org/10.1080/001401300409080

[13] Shakerian, M., Barakat, S., Saber, E. (2025). Risk Management of work-related musculoskeletal disorders using an artificial intelligence approach (narrative review). Journal of Occupational Health Epidemiology, 14(3): 214-225. https://doi.org/10.61882/johe.14.3.214

[14] Waters, T.R., Putz-Anderson, V., Garg, A., Fine, L.J. (1993). Revised NIOSH equation for the design and evaluation of manual lifting tasks. Ergonomics, 36(7): 749-776. https://doi.org/10.1080/00140139308967940

[15] Donisi, L., Jacob, D., Guerrini, L., Prisco, G., Esposito, F., Cesarelli, M., Gargiulo, P. (2023). SEMG spectral analysis and machine learning algorithms are able to discriminate biomechanical risk classes associated with manual material liftings. Bioengineering, 10(9): 1103. https://doi.org/10.3390/bioengineering10091103

[16] Song, J., Qu, X., Chen, C.H. (2016). Simulation of lifting motions using a novel multi-objective optimization approach. International Journal of Industrial Ergonomics, 53: 37-47. https://doi.org/10.1016/j.ergon.2015.10.002

[17] Brandl, C., Brunner, O., Marzaroli, P., Hellig, T., Johnen, L., Mertens, A., Nitsch, V. (2022). Using real-time feedback of L5/S1 compression force based on markerless optical motion capture to improve the lifting technique in manual materials handling. International Journal of Industrial Ergonomics, 91: 103350. https://doi.org/10.1016/j.ergon.2022.103350

[18] Faber, G.S., Kingma, I., Bakker, A.J., Van Dieën, J.H.

(2009). Low-back loading in lifting two loads beside the body compared to lifting one load in front of the body. Journal of biomechanics, 42(1): 35-41. 10.1016/j.jbiomech.2008.10.013
[19] Balcı, S.G., Ersöz, S., Lüy, M., Türker, A.K., Barışçı, N. (2023). Optimization of indoor thermal comfort values with fuzzy logic and genetic algorithm. Journal of Intelligent & Fuzzy Systems, 45(2): 2305-2317. https://doi.org/10.3233/JIFS-223955
[20] González Fuentes, A., Busto Serrano, N.M., Sánchez Lasheras, F., Fidalgo Valverde, G., Suarez Sanchez, A. (2020). Prediction of health-related leave days among workers in the energy sector by means of genetic algorithms. Energies, 13(10): 2475. https://doi.org/10.3390/en13102475
[21] Sharkawy, A.N. (2023). Task location to improve human–robot cooperation: A condition number-based approach. Automation, 4(3): 263-290. https://doi.org/10.3390/automation4030016
[22] Xuan, D.T., Huynh, T.V., Hung, N.T., Thang, V.T. (2023). Applying digital twin and multi-adaptive genetic algorithms in human–robot cooperative assembly optimization. Applied Sciences, 13(7): 4229. https://doi.org/10.3390/app13074229
[23] Haider, M., Hashmi, M.S.A., Raza, A., Ibrahim, M., Fitriyani, N.L., Syafrudin, M., Lee, S.W. (2024). Novel ensemble learning algorithm for early detection of lower back pain using spinal anomalies. Mathematics, 12(13): 1955. https://doi.org/10.3390/math12131955
[24] Qing, L., Su, B., Jung, S., Lu, L., Wang, H., Xu, X. (2024). Predicting human postures for manual material handling tasks using a conditional diffusion model. IEEE Transactions on Human-Machine Systems, 54(6): 723-732. https://doi.org/10.1109/THMS.2024.3472548
[25] Ji, X., Hettiarachchige, R.O., Littman, A.L., Lavery, N.L., Piovesan, D. (2023). Prevent workers from injuries in the Brewing Company via using digital human modelling technology. Applied Sciences, 13(6): 3593. https://doi.org/10.3390/app13063593
[26] Kumar, S. (2007). Biomechanics in Ergonomics, 2nd ed., CRC Press, Boca Raton. https://www.routledge.com/Biomechanics-in-Ergonomics/Kumar/p/book/9780849379086.
[27] Fox, R.R., Lu, M.L., Occhipinti, E., Jaeger, M. (2019). Understanding outcome metrics of the revised NIOSH lifting equation. Applied Ergonomics, 81: 102897. https://doi.org/10.1016/j.apergo.2019.102897
[28] Waters, T.R., Putz-Anderson, V., Garg, A. (1994). Applications manual for the revised NIOSH lifting equation. https://stacks.cdc.gov/view/cdc/5434/cdc_5434_DS1.pdf.
[29] Varrecchia, T., Chini, G., Serrao, M., Ranavolo, A. (2024). Lifting activities assessment using lumbosacral compression and shear forces. Applied Sciences, 14(14): 6044. https://doi.org/10.3390/app14146044
[30] Sláma, D., Mergl, V., Pavlíková, E.A. (2023). Analysis of the heart rate of operators of forwarding machines during work activities. Forests, 14(7): 1348. https://doi.org/10.3390/f14071348
[31] Zaman, R., Xiang, Y., Cruz, J., Yang, J. (2021). Two-dimensional versus three-dimensional symmetric lifting motion prediction models: A case study. Journal of Computing and Information Science in Engineering, 21(4): 044501. https://doi.org/10.1115/1.4049217
[32] Nail-Ulloa, I., Zabala, M., Sesek, R., Chen, H., Schall Jr, M.C., Gallagher, S. (2024). Estimating compressive and shear forces at L5-S1: Exploring the effects of load weight, asymmetry, and height using optical and inertial motion capture systems. Sensors, 24(6): 1941. https://doi.org/10.3390/s24061941