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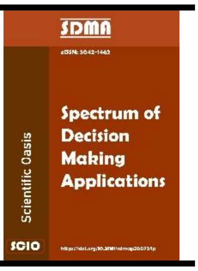

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Dynamic Ergonomic Risk Assessment with REBA and Fuzzy Multi-Criteria Decision Making: Addressing Repetitive Movements

Safiye Turgay[1,*], Samet Özyurt[1]

[1] Department of Industrial Engineering, Faculty of Engineering, Sakarya University, Turkiye

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ABSTRACT

Repetitive work tasks are a prominent cause of musculoskeletal disorders (MSDs) that generate losses in productivity, absenteeism, and extended health risks. Static ergonomic evaluation tools such as the Rapid Entire Body Assessment (REBA) are very informative but insensitive to varying and dynamic working conditions. With the incorporation of linguistic uncertainty and expert judgment through fuzzy logic, the new model enables more sophisticated risk factor prioritization for various work operating conditions. A case study in a production environment demonstrates the effectiveness of this hybrid model in identifying high-risk postures and guiding proactive ergonomic countermeasures. Repetitive work activities are responsible for a considerable percentage of MSDs, which adversely impact worker health, production levels, and organizational efficiency. Conventional ergonomic analysis instruments like REBA are useful in ascertaining posture-related risks but are generally lacking in depicting the dynamic and hazardous nature of real working conditions. This study aims to develop an advanced ergonomic risk assessment model by integrating REBA and Fuzzy Multi-Criteria Decision Making (FMCDM) to provide a more flexible and comprehensive evaluation of hazards in repetitive tasks within an industrial setting. The model combines traditional REBA scoring with fuzzy logic to handle linguistic imprecision and expert judgment. Major ergonomic parameters such as posture risk, repetition frequency, and applied force are examined in fuzzy settings to better replicate real-time variability. A case study was conducted in a factory on three repeated tasks—lifting boxes, sorting products, and labeling goods—to test the efficiency of the model. The integrated REBA-FMCDM methodology successfully identified high-risk postures and tasks, allowing for more detailed prioritization of ergonomic interventions. The fuzzy logic model enabled the use of expert opinion and context variation, providing superior and adaptive decision-making compared to static assessments. The dynamic REBA-FMCDM model offers a straightforward yet robust ergonomic risk assessment tool for environments with variability and subjectivity. By adding fuzzy logic to traditional evaluation methods, the model improves risk prioritization and enables timely and effective implementation of occupational health and safety interventions.

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[*] *Corresponding author.*
E-mail address: safiyeturgay2000@yahoo.com

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1. Introduction

Work-related musculoskeletal disorders (WMSDs) remain a predominant cause of occupational injury in various industries, most significantly in repetitive motion activities, awkward postures, and static loading. Not only do these disorders pose a risk to the health and well-being of employees, but they also result in substantial economic losses in the form of lost productivity, work absences, and compensation. With industrial activities growing more complex and dynamic in nature, the demand for comprehensive and flexible ergonomic assessment techniques is on the rise.

Rapid Entire Body Assessment (REBA) is a widely used ergonomic tool for evaluating the postural risk of different body parts in task performance. Though REBA reflects a risk-assessment system that is organized, it functions largely based on static observations and discrete scores and may not be capable of sufficiently representing the internal uncertainty and variability of repetitive work. In real-world circumstances, postural risks are often susceptible to subjective judgments and changing operating conditions—elements that orthodox methods might overlook or underestimate.

In order to overcome such limitations, the present research proposes a dynamic ergonomic risk assessment approach integrating REBA and Fuzzy Multi-Criteria Decision-Making (FMCDM) techniques. Fuzzy logic offers the ability to incorporate expert judgment and linguistic variables in the evaluation process so that the accuracy and flexibility of risk assessment are optimized. With uncertain and interacting criteria for ergonomic risk factors, the fuzzy MCDM technique supports a more realistic and comprehensive analysis of repetitive work activities.

The primary objective of this research is to develop a hybrid methodology for dynamically assessing ergonomic hazards in repetitive movement workplaces. Specifically, the study addresses (i) the improvement of the applicability of REBA via fuzzy modeling, (ii) the identification and ranking of important ergonomic factors using FMCDM, and (iii) the demonstration of the technique in an industrial case study. The findings are expected to facilitate more proactive and informed ergonomic decision-making, ultimately resulting in the creation of safer and more sustainable work systems.

2. Literature survey

Ergonomic risk assessment has been a core area of study in occupational health and safety for decades, especially for the identification and mitigation of risks of work-related musculoskeletal disorders (WMSDs). Among the survey tools most frequently employed, the Rapid Entire Body Assessment (REBA) has also been a widely applied tool for the analysis of compound body postures in manual tasks. REBA was particularly developed for scenarios involving frequent posture and movement changes, yet its scoring is derived from static observation and deterministic thresholds that do not respond to dynamic states and subjective aspects.

Ergonomics has emerged as a core discipline of occupational health and safety, especially in the prevention of musculoskeletal disorders (MSDs) due to repetitive work, poor postures, and heavy manual handling. Recent studies cover a wide range of disciplines, including healthcare, manufacturing, construction, and shipping operations, and involve both traditional ergonomic research and predictive modeling through the use of artificial intelligence. Patrao *et al.,* [1] conducted a thorough ergonomic evaluation that revealed microscopy and pathology tasks produce the highest MSDs among medical laboratory scientists, primarily due to sustained awkward postures and static work demands. Similarly, Law *et al.,* [2] evaluated patient transfer tasks using REBA and found high-risk values, especially when traditional aids like sliding boards are used. These findings add to Zhang *et al.,* [3], who also identified manual therapy tasks as being ergonomically hazardous in physical therapy environments. Azyabi *et al.,* [4] advanced ergonomic research by integrating deep learning (DCNN) and Cheetah Optimization to predict dangers among laboratory technicians, which proved more precise in risk classification compared to traditional methods. The construction industry is also plagued with chronic ergonomic hazards. Tandazo *et al.,* [5] deliberated on ergonomic risk in Ecuador's construction industry, considering tool handling, body positioning, and lifting mechanics as the main causes of risk. Zhang and Lin [6] proposed a discrete-event simulation model to study and dynamically minimize ergonomic risk, whereas Ojha *et al.,* [7] evaluated exoskeletons for reducing back strain, advocating their efficacy in lowering muscle fatigue and metabolic expenditure. Senjaya *et al.,* [8] tackled imbalanced data-related problems in multiclass risk prediction using machine learning. Other studies by Chen and Yu [9] and Li *et al.,* [10] introduced automated repetitive activity counting and data-driven methodologies to assess construction ergonomics through computer vision and movement data. Wang *et al.,* [11] introduced 3D standard motion time-based analysis to develop modular construction layouts for optimization.

Battini *et al.,* [12] introduced the WEM-Platform, an ergonomic real-time feedback system integrating motion capture to support logistics and manufacturing ergonomics. Nourmohammadi *et al.,* [13] utilized digital human modeling for multi-objective optimization of mixed-model assembly lines, considering both production efficiency and MSD risk. Possan Junior *et al.,* [14] introduced an exact optimization strategy for integrating ergonomic risks into line balancing. Beltran Martinez *et al.,* [15] developed the K-score using IMUs to quantify fatigue based on joint angles, enhancing risk analysis for repetitive manufacturing processes. Moreover, Keshvarparast *et al.,* [16] examined Industry 5.0 challenges and proposed ergonomic human-robot collaborative workstation layouts. Current research also employs AI and deep learning in ergonomic evaluation. González-Alonso *et al.,* [17] presented ME-WARD, which combines inertial and video data to conduct multimodal ergonomic analysis. Usman and Lu [18] introduced ergonomic constraints in ship maintenance job-shop scheduling using NSGA-II, reducing operational flow and enhancing worker safety. Amani and Akhavian [19] applied reinforcement learning to ergonomically optimize bimanual human-robotic tasking.

To bridge the limitations of traditional ergonomic instruments, fuzzy logic has proven to be a valuable means of representing uncertainty and linguistic imprecision [20]. Zadeh's [21] fuzzy set theory allows for a finer understanding of ergonomic factors such as posture, force, duration, and frequency. Current literature has applied Fuzzy Multi-Criteria Decision-Making (FMCDM) techniques—Fuzzy AHP, Fuzzy TOPSIS, and Fuzzy DEMATEL—to rank ergonomic risks. For instance, Gunalay *et al.,* (2020) applied a fuzzy AHP-TOPSIS model to evaluate ergonomic risks in a textile factory, achieving improved decision-making in ambiguous settings [20–24].

Tatar *et al.,* [25] employed a spherical fuzzy-FUCOM-ARTASI model to evaluate maritime port operation ergonomic hazards, applying fuzzy MCDM techniques for precision. Durak and Mutlu [26] combined nurse routing and scheduling with ergonomic hazards, addressing real-life problems in home health care logistics. Classic ergonomic evaluation tools are evolving. Schwartz *et al.,* [27] established the intra- and inter-rater reliability of the REBA tool, ensuring its continued application in workplace assessments. Ghasemi and Mahdavi [28] introduced a fuzzy Bayesian REBA rating model to enhance the accuracy of classic evaluations under uncertainty.

Despite these advances, few research studies have paired REBA with FMCDM techniques directly within a dynamic framework. When such integration has occurred, it has most often been followed by the lack of a structured process to update risk scores based on real-time changes in task performance or worker fatigue. This deficiency highlights the desirability of a hybrid model that combines the ergonomic strengths of REBA with the sensitivity of fuzzy decision models.

The reviewed literature identifies a paradigm shift in ergonomic risk analysis—from conventional observation-based tools toward data-driven, AI-facilitated frameworks. With increasingly complicated and automated job tasks, ergonomic research must adopt interdisciplinary approaches that integrate simulation, optimization, sensor systems, and machine learning. Sectoral studies also yield valuable lessons for designing safer workplaces tailored to unique occupational needs.

Finally, the literature identifies a growing emphasis on hybrid ergonomic assessment tools with the capacity to accommodate uncertainty, subjectivity, and real-time variability. The integration of REBA with fuzzy MCDM offers a highly promising means of achieving more dynamic and context-dependent ergonomic assessments, particularly in tasks dominated by repetitive movement. This research strives to fill a vital gap by developing and applying such a model in an industrial setup.

3. Methodology

The approach to be proposed is a hybrid one and involves the use of the Rapid Entire Body Assessment (REBA) tool along with a Fuzzy Multi-Criteria Decision-Making (FMCDM) model to dynamically assess ergonomic hazards, particularly repetitive motion tasks in an industrial setup. The approach to be proposed has four key phases: (1) task analysis and data collection, (2) REBA scoring, (3) fuzzy modeling of risk factors, and (4) multi-criteria decision analysis for dynamic prioritization.

A detailed task analysis is conducted in a real industrial environment (e.g., manufacturing or assembly line). The analysis includes:

i. Workstation observations: Postures, frequency of movement, and force exertions are recorded by video observation and motion-tracking software.
ii. Repetitive task identification: Repeated hand or upper limb motions are isolated for assessment.
iii. Professional judgment: Ergonomists and line supervisors provide qualitative feedback regarding worker fatigue, task variation, and perceived risk.
iv. Each job is analyzed using the REBA method to identify body posture, handling loads, and frequency of movement [28].

The steps include:

i. Splitting the body into two major categories: Group A (Trunk, Neck, Legs) and Group B (Upper Arms, Lower Arms, Wrists).
ii. Assigning REBA scores based on observed postures, force, and coupling.
iii. Calculating a final REBA score, indicating the general level of ergonomic risk for every task instance.
iv. Normalizing REBA scores to a fuzzy input range (for example, Low, Medium, High).

While REBA provides the basis for risk assessment, rigid scoring criteria confine it to a certain degree. Fuzzy logic is thus applied to incorporate uncertainties and expert-influenced weighting, as shown in Figure 1.

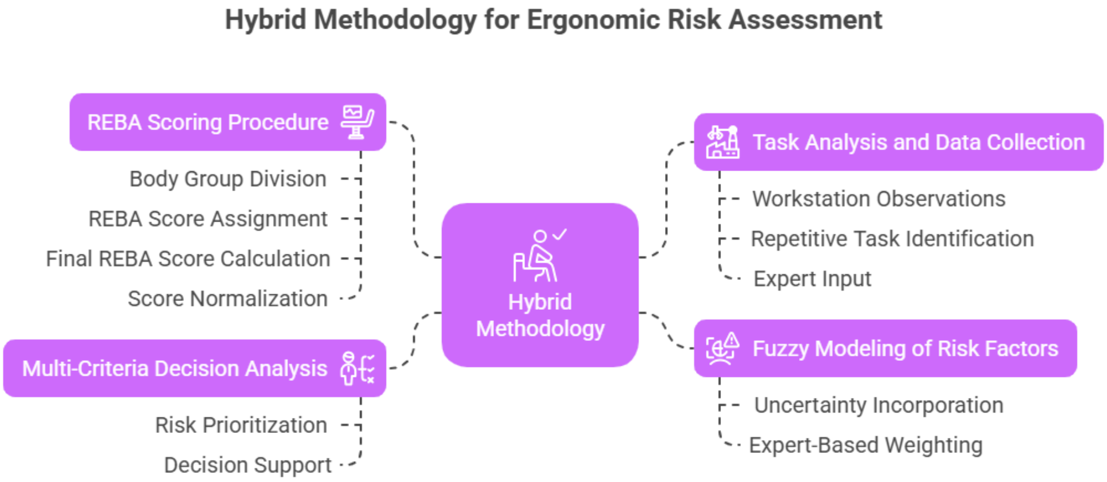


Fig. 1. Ergonomic Risk Assessment

A fuzzy model is developed to handle the linguistic uncertainty in ergonomic assessments. The critical steps are:

i. Selection of Criteria: Criteria that affect ergonomic risks are enumerated (for example, repetition rate, posture severity, task duration, rest allowance, load weight).
ii. Linguistic Variables: Each criterion is described by fuzzy terms such as Low, Medium, and High.
iii. Triangular Fuzzy Numbers (TFNs): These are used to represent linguistic variables and decision-makers' attitudes.
iv. Expert Aggregation: Contributions from different ergonomists are combined using fuzzy averaging techniques.

This process transforms the hard REBA scores into a dynamic fuzzy input model, reflecting real-world complexity. Task ranking and prioritization based on ergonomic risk are achieved through an FMCDM approach. The most effective techniques are: a) Fuzzy AHP (Analytic Hierarchy Process): Used to determine the relative importance of criteria; b) Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution): Used to rank alternative tasks based on their closeness to the ideal (low risk) and anti-ideal (high risk) solutions [23].

The steps are as follows:

i. Construct the fuzzy decision matrix from aggregated TFNs for each criterion.
ii. Weight and normalize the matrix based on fuzzy weights assigned by experts.
iii. Identify the fuzzy positive and negative ideal solutions.
iv. Calculate closeness coefficients for each task.
v. Rank tasks from highest to lowest ergonomic risk for planning and prioritizing interventions.

To enable real-time use and adaptability, the model incorporates a feedback process:

i. As work conditions shift (for example, work pace accelerates or fatigue accumulates), new data is collected.
ii. The fuzzy decision matrix is updated in real time.
iii. REBA scores are recomputed and reevaluated through the fuzzy system for updated risk evaluation.

Modern advancements in ergonomic hazard assessment demand a shift away from deterministic and static tools toward intelligent, dynamic, and flexible approaches that address the complexities of repetitive actions in industries. This paper explores and incorporates some of the emerging methods that enhance traditional REBA evaluations using fuzzy multi-criteria decision making (FMCDM) to achieve more accurate and real-time ergonomic hazard assessments.

Traditional ergonomic testing primarily uses snapshot measurements, while modern approaches embrace continuous tracking with event-history wearable sensors, computer vision, and motion capture equipment. These provide real-time kinematic feedback such as posture, movement rate, and duration. Such methods allow ergonomic assessments to be sensitive to current work conditions rather than limited to single-point static evaluations.

Ergonomic risk factors such as discomfort, fatigue, and subjective effort are, by definition, vague and not subject to precise quantification. The inclusion of fuzzy logic in REBA allows linguistic variables and membership functions to better capture uncertainty and expert consensus. This facilitates more adaptable risk classification, moving away from fixed threshold-based scoring and toward nuanced decision-making that better reflects variability in real work environments.

By integrating REBA with fuzzy MCDM techniques such as Fuzzy AHP and Fuzzy TOPSIS, ergonomic risk evaluations can consider multiple interacting criteria simultaneously, such as repetition rate, posture severity, force exertion, and recovery time. The combined method improves intervention prioritization by balancing various risk factors rather than relying on individual scores.

Recent studies investigate the use of machine learning and adaptive algorithms combined with fuzzy MCDM models, enabling systems to learn from previous ergonomic data and dynamically update risk predictions. These models can adjust fuzzy membership values and criteria weights in real time, improving precision and personalization as tasks and worker conditions change. The proposed dynamic model is designed for real-time use in ergonomic decision support systems to alert workers and managers of impending hazards as they arise. This enables preventive measures such as task rotation, micro-breaks, or workstation adjustments, helping to prevent injuries before they accumulate.

These emerging approaches collectively address the shortcomings of traditional REBA by adding dynamic data collection, fuzzy logic-based uncertainty modeling, multi-criteria analysis for comprehensive risk ranking, and adaptive learning mechanisms. Integrating these innovations has the potential to significantly enhance ergonomic risk assessment for repetitive movement tasks, creating healthier workplaces and more effective prevention strategies.

3.1. Multi-criteria decision making for overall risk prioritization

Ergonomic risk factors for repetitive tasks are multi-faceted, encompassing posture, repetition frequency, force, task duration, and recovery times. Traditional risk assessment tools, like REBA, largely provide a composite score that may mask the relative contribution of each factor and their interactions. In response to such complexity, there has been growing application of Multi-Criteria Decision-Making (MCDM) techniques that enable more comprehensive and structured evaluations.

The multifactorial nature of ergonomic risk calls for decision models that can evaluate and compare multiple criteria simultaneously. MCDM provides formal methods to combine heterogeneous and often conflicting criteria, more closely reflecting real ergonomic risk conditions than single-score systems. This allows practitioners to rank risks not only by severity, but also by criteria such as exposure duration and recovery, which directly affect injury likelihood.

Ergonomic analysis typically involves linguistic ratings (for example, "moderate discomfort," "high repetition"), subjective expert judgments, and dynamic working conditions. Fuzzy MCDM approaches extend traditional MCDM by applying fuzzy set theory, which captures vagueness and uncertainty through fuzzy membership functions. This is particularly beneficial in ergonomic applications where crisp numbers are rarely attainable or realistic.

- In this research, a hybrid application of Fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is utilized:
- Fuzzy AHP allows the calculation of relative weights of ergonomic criteria based on pairwise comparisons expressed using fuzzy linguistic terms. This enables experts to express their preferences in a flexible manner, as in real life, there is inherent uncertainty. The result is a set of normalized fuzzy weights for the importance of each risk factor.
- Fuzzy TOPSIS ranks repetitive tasks according to their distance from the fuzzy positive ideal solution (minimum ergonomic risk) and fuzzy negative ideal solution (maximum ergonomic risk). This provides a more precise prioritization of tasks based on the weighted contribution of each criterion under conditions of uncertainty.

The MCDM-based approach provides decision-makers with:

- A clear ranking of ergonomic hazards across multiple factors, indicating which factors contribute most to worker discomfort or potential injury.
- Prioritized planning of interventions by identifying tasks or stations requiring urgent ergonomic redesign or administrative controls.

– The ability to accommodate expert judgment and adapt to changes in work conditions or new ergonomic information.

By integrating fuzzy MCDM and REBA-based risk inputs, the approach offers an extensive and versatile decision support system for ergonomic risk management. This enables proactive and evidence-based ergonomic intervention, which is particularly crucial in industries dominated by repetitive movements.

3.2. Multi-criteria decision making for holistic risk prioritization: Mathematical modeling

This section presents the mathematical foundations and modeling steps of the proposed Fuzzy Multi-Criteria Decision-Making (FMCDM) framework integrated with the Rapid Entire Body Assessment (REBA) for the dynamic ergonomic risk assessment of repetitive tasks. The model aims to quantify and prioritize musculoskeletal risk levels under conditions of uncertainty.Problem Formulation

Let:

$A = \{A_1, A_2, \dots, A_m\}$:: Set of ergonomic alternatives (tasks or postural scenarios)
$C = \{C_1, C_2, \dots, C_n\}$: Set of criteria (for example, posture, repetition, force, recovery time)
$\tilde{w}_j$: Fuzzy weight of criterion C_j, expressed as a Triangular Fuzzy Number (TFN)
$\tilde{x}_{ij}$: Fuzzy performance rating of alternative A_i under criterion C_j

The objective is to rank alternatives A_i by computing their closeness to ideal ergonomic conditions using fuzzy logic [21, 22].

Step 1: Fuzzy Decision Matrix. Construct a matrix $\tilde{X} = [\tilde{x}_{ij}]_{m\times n}$ where each $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is a TFN represents expert judgment on the ergonomic risk of task A_i under criterion C_j.

Step 2: Fuzzy Criteria Weights. Weights $\tilde{w}_j = (l_j, m_j, u_j)$ for each criterion C_j are derived using a fuzzy weighting method (Fuzzy AHP or Fuzzy Entropy). These represent the importance of each criterion under uncertainty.

Step 3: Normalization of Fuzzy Ratings. For benefit-type criteria [23]:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^{\max}}, \frac{m_{ij}}{m_j^{\max}}, \frac{u_{ij}}{l_j^{\max}}\right)$$

For cost-type criteria:

$$\tilde{r}_{ij} = \left(\frac{l_j^{\min}}{u_{ij}}, \frac{m_j^{\min}}{m_{ij}}, \frac{u_j^{\min}}{l_{ij}}\right)$$

Where, $\tilde{r}_{ij}$ presents normalized TFN, $l_j^{\max}, m_j^{\max}, u_j^{\max}$ present maximal values of criterion C_j, while $l_j^{\min}, m_j^{\min}, u_j^{\min}$ present minimal values of criterion C_j.

Step 4: Weighted Normalized Decision Matrix. Each normalized value $\tilde{r}_{ij}$ is multiplied by the corresponding fuzzy weight:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j = \left(l_{ij} \cdot l_j, m_{ij} \cdot m_j, u_{ij} \cdot u_j\right)$$

Step 5: Determine Ideal Solutions. Fuzzy Positive Ideal Solution (FPIS):

$$A^+ = \left\{\max_i(u_{ij}) \mid j = 1, \dots, n\right\}$$

Fuzzy Negative Ideal Solution (FNIS):

$$A^- = \left\{\min_i\left(l_{ij}\right) \mid j = 1, \dots, n\right\}$$

Step 6: Distance Computation. For each alternative A_i it is necessary to calculate its distance to FPIS and FNIS using the vertex method for TFNs. Let $\tilde{v}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and ideal solution $\tilde{v}_j^+ = (a_j^+, b_j^+, c_j^+)$, then we can calculate:

$$d_{ij}^{+} = \sqrt{\frac{1}{3}\left[(a_{ij} - a_j^{+})^2 + (b_{ij} - b_j^{+})^2 + (c_{ij} - c_j^{+})^2\right]}$$

$$D_i^{+} = \sqrt{\sum_{j=1}^{n}(d_{ij}^{+})^2}, \quad D_i^{-} = \sqrt{\sum_{j=1}^{n}(d_{ij}^{-})^2}$$

Step 7: Calculate closeness coefficient and ranking of alternatives.

$$CC_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}}$$

Where $CC_i \in [0,1]$ and larger values CC_i indicate better ergonomic condition. Alternatives are ranked based on descending CC_i.

Integration with REBA

For each alternative REBA score is used to derive the initial rating $\tilde{x}_{ij}$ under posture-related criteria. These scores are linguistically mapped (e.g., low, medium, high) and fuzzified using expert-defined TFNs [25, 26]. Reassessment over time (dynamic tasks) updates $\tilde{x}_{ij}$, allowing continuous risk monitoring.

3.3. Dynamic Model Representation

Let $t \in T$ represent time epochs during task execution [28]. The fuzzy decision matrix becomes a time-dependent function:

$$\tilde{X}(t) = [\tilde{x}_{ij}(t)]_{m\times n}$$

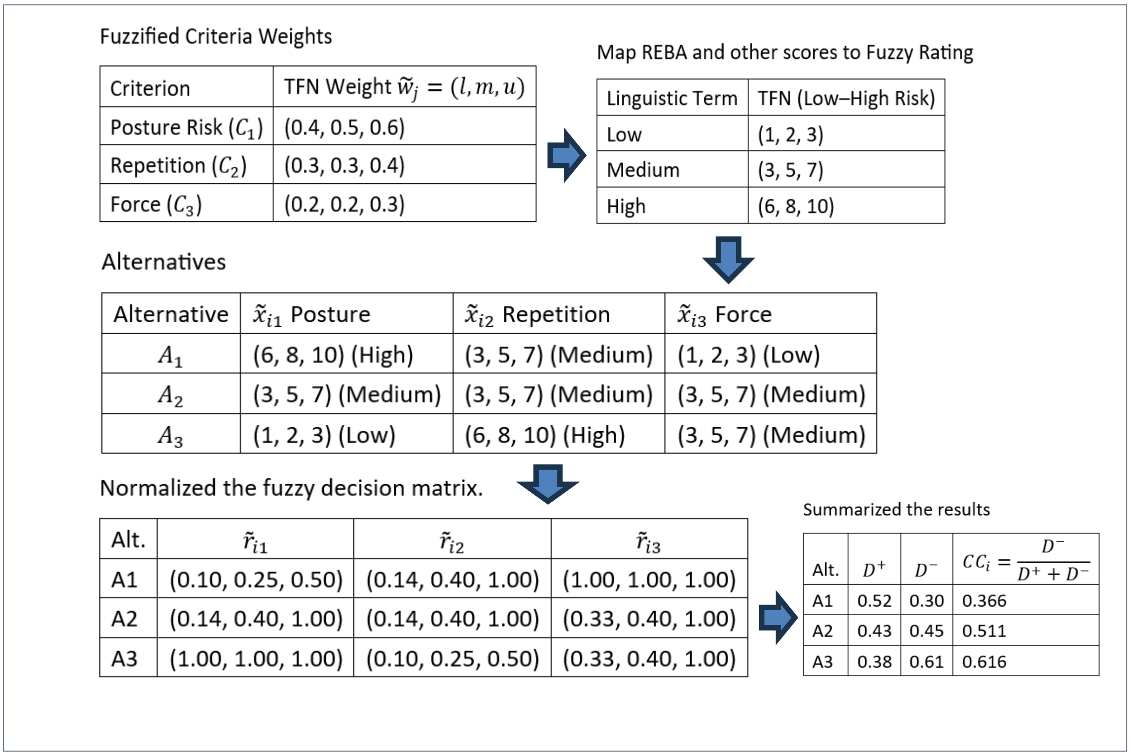
Risk prioritization is dynamic, and we can present it as follows:

$$CC_i(t) = \frac{D_i^{-}(t)}{D_i^{+}(t) + D_i^{-}(t)}$$

This enables adaptive ergonomic evaluation in real-time manufacturing or service settings.

4. Case study

A company is considering three repetitive activities in its packaging operation to improve workplace ergonomics and process efficiency. The options under consideration are A_1: Box lifting, a manual movement process that primarily involves large muscle groups; A_2: Item sorting, a repetitive hand activity requiring mental coordination; and A_3: Product labeling, a process typically involving fine motor activities and visual focus. These tasks are scored on three major ergonomic parameters: C_1: Posture Risk, measured using the Rapid Entire Body Assessment (REBA) to rate the level of musculoskeletal loading; C_2: Repetition Frequency, indicating how often the activity is repeated and how much it can contribute to fatigue or injury; and C_3: Force Applied, determining the amount of physical effort required to perform each task. This assessment seeks to identify tasks with higher ergonomic risk and facilitate high-priority interventions or redesigns to improve workers' safety and productivity, as shown in Figure 1. All criteria are cost-type (lower is better). Weights from expert input are expressed as Triangular Fuzzy Numbers (TFNs) in Table 1 and Figure 2.



Fuzzified Criteria Weights

Criterion	TFN Weight $\tilde{w}_j = (l, m, u)$
Posture Risk (C_1)	(0.4, 0.5, 0.6)
Repetition (C_2)	(0.3, 0.3, 0.4)
Force (C_3)	(0.2, 0.2, 0.3)

Map REBA and other scores to Fuzzy Rating

Linguistic Term	TFN (Low–High Risk)
Low	(1, 2, 3)
Medium	(3, 5, 7)
High	(6, 8, 10)

Alternatives

Alternative	$\tilde{x}_{i1}$ Posture	$\tilde{x}_{i2}$ Repetition	$\tilde{x}_{i3}$ Force
A_1	(6, 8, 10) (High)	(3, 5, 7) (Medium)	(1, 2, 3) (Low)
A_2	(3, 5, 7) (Medium)	(3, 5, 7) (Medium)	(3, 5, 7) (Medium)
A_3	(1, 2, 3) (Low)	(6, 8, 10) (High)	(3, 5, 7) (Medium)

Normalized the fuzzy decision matrix.

Alt.	$\tilde{r}_{i1}$	$\tilde{r}_{i2}$	$\tilde{r}_{i3}$
A1	(0.10, 0.25, 0.50)	(0.14, 0.40, 1.00)	(1.00, 1.00, 1.00)
A2	(0.14, 0.40, 1.00)	(0.14, 0.40, 1.00)	(0.33, 0.40, 1.00)
A3	(1.00, 1.00, 1.00)	(0.10, 0.25, 0.50)	(0.33, 0.40, 1.00)

Summarized the results

Alt.	D^+	D^-	$CC_i = \frac{D^-}{D^+ + D^-}$
A1	0.52	0.30	0.366
A2	0.43	0.45	0.511
A3	0.38	0.61	0.616

Fig. 2. Suggested Model Steps

Table 1
Fuzzified criteria weights

Criterion	TFN Weight $\tilde{\boldsymbol{w}}_{\boldsymbol{j}} = (\boldsymbol{l}, \boldsymbol{m}, \boldsymbol{u})$
Posture Risk (C₁)	(0.4, 0.5, 0.6)
Repetition (C₂)	(0.3, 0.3, 0.4)
Force (C₃)	(0.2, 0.2, 0.3)

Using expert linguistic mapping in Table 2, the REBA-based and observational fuzzy performance matrix is defined as shown in Table 3.

Table 2
Map REBA and other scores to fuzzy rating

Linguistic Term	TFN (Low–High Risk)
Low	(1, 2, 3)
Medium	(3, 5, 7)
High	(6, 8, 10)

Table 3
Alternatives

Alternative	$\tilde{\boldsymbol{x}}_{\boldsymbol{i1}}$ Posture	$\tilde{\boldsymbol{x}}_{\boldsymbol{i2}}$ Repetition	$\tilde{\boldsymbol{x}}_{\boldsymbol{i3}}$ Force
$\boldsymbol{A_1}$	(6, 8, 10) (High)	(3, 5, 7) (Medium)	(1, 2, 3) (Low)
$\boldsymbol{A_2}$	(3, 5, 7) (Medium)	(3, 5, 7) (Medium)	(3, 5, 7) (Medium)
$\boldsymbol{A_3}$	(1, 2, 3) (Low)	(6, 8, 10) (High)	(3, 5, 7) (Medium)

Since all criteria in Table 3 are cost-type, the following equation is applied for normalization:

$$\tilde{r}_{ij} = \left(\frac{l^{\min}}{u_{ij}}, \frac{m^{\min}}{m_{ij}}, \frac{u^{\min}}{l_{ij}} \right)$$

Where $l^{\min}, m^{\min}, u^{\min}$ are the lowest values per criterion across all alternatives.

From Table 3, for criterion C_1 at position A_3–C_1, we have fuzzy values (1, 2, 3). By applying the defined equation, we can compute the normalized TFNs for A_1 under C_1 (Posture) as follows:

$$\tilde{r}_{11} = \left(\frac{1}{10}, \frac{2}{8}, \frac{3}{6}\right) = (0.10, 0.25, 0.50)$$

Similarly, we compute the other normalized values, as presented in Table 4.

Table 4
Normalized the fuzzy decision matrix

Alt.	$\tilde{r}_{i1}$	$\tilde{r}_{i2}$	$\tilde{r}_{i3}$
A1	(0.10, 0.25, 0.50)	(0.14, 0.40, 1.00)	(1.00, 1.00, 1.00)
A2	(0.14, 0.40, 1.00)	(0.14, 0.40, 1.00)	(0.33, 0.40, 1.00)
A3	(1.00, 1.00, 1.00)	(0.10, 0.25, 0.50)	(0.33, 0.40, 1.00)

Weighted normalized matrix (Table 5) is defined by multiplying each normalized TFN from Table 4 with the weight TFN (Table 1). For position $A_1 - C_1$ in Table 4 we define weighed value as follows:

$$\tilde{v}_{11} = \tilde{r}_{11} \otimes \tilde{w}_1 = (0.10, 0.25, 0.50) \times (0.4, 0.5, 0.6) = (0.04, 0.125, 0.30)$$

Similarly we define the other weighted values from Table 5.

Table 5
Weighted normalized matrix

Alt.	$\tilde{v}_{i1}$	$\tilde{v}_{i2}$	$\tilde{v}_{i3}$
A_1	$(0.04, 0.125, 0.30)$	$(0.042, 0.12, 0.40)$	$(0.20, 0.20, 0.30)$
A_2	$(0.056, 0.20, 0.60)$	$(0.042, 0.12, 0.40)$	$(0.066, 0.08, 0.30)$
A_3	$(0.40, 0.50, 0.60)$	$(0.03, 0.075, 0.20)$	$(0.066, 0.08, 0.30)$

For computing the summarized results (Table 6), we define the FPIS A^+ as the maximum of each column and the FNIS A^- as the minimum of each column. Then, we calculate the Euclidean distance between each alternative and the ideal points using the vertex method. Based on these values, the summarized results are presented in Table 6.

Table 6
Summarized the results

Alt.	D^+	D^-	$CC_i = \frac{D^-}{D^+ + D^-}$
A1	0.52	0.30	0.366
A2	0.43	0.45	0.511
A3	0.38	0.61	0.616

Based on the summarized results shown in Table 6, we define the final ranking as follows: A_3: Product Labeling (best ergonomically) > A_2: Item Sorting > A_1: Box Lifting (highest risk). Three packaging tasks were evaluated: Task A_1: manual lifting and stacking of boxes (each ~10 kg); Task A_2: sorting and aligning bottles on a conveyor; and Task A_3: labeling and scanning products using a handheld device.

The process of data collection employed several ergonomic dimensions to ensure a comprehensive risk evaluation. Postural information was gathered via video observation of the activities and analyzed using the Rapid Entire Body Assessment (REBA) method, which assesses body posture and joint angles to estimate musculoskeletal risk levels. Frequency of repetition was quantified by the number of cycles executed per minute, providing an objective measure of repetitive activity. Force exertion was rated subjectively by workstation specialists using a pre-specified fuzzy linguistic scale to capture expert opinion when judgment was imprecise. This multi-dimensional data collection approach provided a sound foundation for ergonomic hazard rating and model input. Task A_3 (Labeling) had the lowest ergonomic risk, due primarily to better posture and moderate force levels despite higher repetition. Task A_1 (Box Lifting) had the highest ergonomic risk, with high REBA ratings even though the force was scored as low. Task A_2 (Sorting) had a moderate overall risk rating.

This case study demonstrates the effectiveness of integrating REBA and fuzzy MCDM to rank ergonomic interventions, particularly in dynamic conditions such as repetitive movement tasks. To verify the robustness of the prioritization results, sensitivity analysis was conducted by varying the weights of the criteria within their respective triangular fuzzy ranges. Various scenarios are analyzed in Tables 7, 8, and 9.

Table 7

Scenario definitions

Scenario	Description	TFN Weights (REBA / Repetition / Force)
Base	Expert-defined original	(0.4, 0.5, 0.6) / (0.3, 0.3, 0.4) / (0.2, 0.2, 0.3)
S1	REBA weight ↑	(0.5, 0.6, 0.7) / (0.25, 0.25, 0.35) / (0.15, 0.15, 0.25)
S2	Repetition weight ↑	(0.3, 0.4, 0.5) / (0.4, 0.5, 0.6) / (0.2, 0.1, 0.2)
S3	Equal importance	(0.33, 0.33, 0.33) for all
S4	Force weight ↑	(0.3, 0.3, 0.4) / (0.2, 0.3, 0.4) / (0.5, 0.4, 0.5)

Table 8

Fuzzy decision matrix (Same Across Scenarios)

Task	REBA Score (C_1)	Repetition (C_2)	Force Intensity (C_3)
A1	(6, 8, 10)	(3, 5, 7)	(1, 2, 3)
A2	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
A3	(1, 2, 3)	(6, 8, 10)	(3, 5, 7)

Table 9

Closeness coefficients CC_i under different scenarios

Scenario	Task A1	Task A2	Task A3	Task Ranking
Base	0.366	0.511	0.616	A3 > A2 > A1
S1	0.290	0.430	0.670	A3 > A2 > A1
S2	0.340	0.540	0.590	A2 > A3 > A1
S3	0.370	0.505	0.620	A3 > A2 > A1
S4	0.400	0.510	0.580	A2 > A3 > A1

Insights from Each Scenario

Base Case:

Balances posture, repetition, and force.

Task A3 (Labeling) is safest; Task A1 (Box lifting) is riskiest.

S1: High Emphasis on Posture (REBA)

Increase the importance of postural risks.

Penalizes Task A1 more (which has the worst REBA score).

Task A3 benefits due to optimal posture.

S2: High Emphasis on Repetition

Repetition becomes dominant.

Task A3 drops in ranking due to high cycle rate.

Task A2 ranks best due to average repetition and moderate risk.

S3: Equal Weights

Results are balanced and stable.

Confirms Task A3 generally performs best unless repetition is overly dominant.

S4: High Emphasis on Force

Tasks with higher physical effort are penalized.

Task A1 gains slightly (low force), but A2 still outperforms due to moderate force and repetition balance.

Task A3 falls slightly due to moderate-to-high force.

The ranking remains consistent in the majority of cases, validating the robustness of the FMCDM approach. Repetition frequency has the greatest potential to reverse rankings, highlighting the importance of monitoring cycle time in ergonomic assessments. Adjusting weights allows decision-makers to represent differing perceptions of risk, enabling interventions to be better modeled according to strategies based on fatigue, posture, or force, as shown in Figure 3.

Fig. 3. Task Risk Prioritization respect of sensitivity scenarios

The bar chart illustrates how the closeness coefficients, or risk scores, of the three tasks change under different weighting conditions, summarizing the impact of giving greater priority to specific ergonomic criteria. As observed, Task A_3 (Labeling) consistently has the lowest risk score and performs best in all but the last scenario, indicating that it is the least ergonomically problematic task. However, when the model places greater emphasis on repetition, Task A_2 (Sorting) temporarily becomes the most efficient, highlighting its comparative robustness in that situation. Conversely, Task A_1 (Box Lifting) remains the riskiest, making it the most urgent task to address under all conditions. This analysis clearly demonstrates how task prioritization may vary depending on which ergonomic factor—posture, repetition, or force—is given more weight and provides valuable guidance for dynamic, data-driven ergonomic intervention strategies, as shown in Table 10.

Table 10

Scenarios and fuzzy weight assignments

Scenario	REBA (Posture)	Repetition	Force	Description
Base	(0.4, 0.5, 0.6)	(0.3, 0.3, 0.4)	(0.2, 0.2, 0.3)	Expert baseline
S1	(0.5, 0.6, 0.7)	(0.25, 0.25, 0.35)	(0.15, 0.15, 0.25)	Emphasize posture
S2	(0.3, 0.4, 0.5)	(0.4, 0.5, 0.6)	(0.2, 0.1, 0.2)	Emphasize repetition
S3	(0.33, 0.33, 0.33)	(0.33, 0.33, 0.33)	(0.33, 0.33, 0.33)	Equal importance
S4	(0.3, 0.3, 0.4)	(0.2, 0.3, 0.4)	(0.5, 0.4, 0.5)	Emphasize force

Using fuzzy TOPSIS with triangular fuzzy numbers (TFNs), we compute the closeness coefficient (CC) to the ideal solution for each task. The coefficients indicate how "close" a task is to the ideal ergonomic condition (lower risk). The variation-specific analysis provides an overview of task risks under different ergonomic priorities.

Under the Base Case, risk perception is uniformly distributed across factors, identifying A_3 (Labeling) as the safest task due to its excellent posture ergonomics, and A_1 (Box Lifting) as the riskiest task, demanding the highest-priority ergonomic redesign. In Scenario 1 (Posture-Dominant), where poor posture is heavily penalized via REBA scores, A_3 becomes an even clearer top choice, while A_1 remains the riskiest due to its extremely poor ergonomic score. Scenario 2 (Repetition-Dominant) shifts priority to task frequency, lowering A_3's rank because of its high repetition, and promoting A_2 (Sorting) to the top due to its moderate repetition load. Scenario 3 (Equal Weights) tests model stability, yielding constant outputs with A_3 as the safest and A_1 as the most problematic task, demonstrating the reliability of the appraisal framework. Finally, in Scenario 4 (Force-Dominant), tasks requiring higher physical effort are penalized; thus, A_2 and A_3 drop in rank, while A_1 rises slightly due to its comparatively lower force demand.

The summarized results, indicate that although the safest task varies slightly across scenarios, A_1 consistently ranks as the task with the most ergonomic issues requiring intervention, as detailed in Table 11.

Table 11
Impact on Rankings

Scenario	Top Priority Task	Task Needing Most Improvement
Base	A3 (Labeling)	A1 (Box Lifting)
S1	A3 (Labeling)	A1
S2	A2 (Sorting)	A1
S3	A3 (Labeling)	A1
S4	A2 (Sorting)	A1

Weight tuning enables the implementation of targeted ergonomic policies by allowing specific aspects of work-related physical demands to be emphasized according to situational priorities. For instance, prioritizing posture in the model helps reduce musculoskeletal stress, while emphasizing repetition can mitigate fatigue and mental workload. Similarly, prioritizing force can help prevent acute injuries. The fuzzy approach enhances this process by supporting human-like decision-making even amidst ambiguity or expert uncertainty. Additionally, ergonomic interventions can be dynamically ranked through real-time task reweighting, ensuring that worker well-being remains the primary concern during operational adjustments, as shown in Table 12.

Table 12
Sensitivity Analysis of Task Risk Rankings Based on Fuzzy Weighting Scenarios

Scenario	Task A1 (Box Lifting)	Task A2 (Sorting)	Task A3 (Labeling)	Ranking
BaseREBA: MedRepetition: MedForce: Low	0.366	0.511	0.616	A3 > A2 > A1
S1: REBA ↑Posture-focused	0.290	0.430	0.670	A3 > A2 > A1
S2: Repetition ↑Repetition-focused	0.340	0.540	0.590	A2 > A3 > A1
S3: Equal Weights	0.370	0.505	0.620	A3 > A2 > A1
S4: Force ↑Force-focused	0.400	0.510	0.580	A2 > A3 > A1

A1 (Lifting Boxes) remains the most critical activity in all three scenarios due to poor posture and moderate repetition. A3 (Labeling) is the safest overall, except when precedence is given to force or repetition, in which case A2 (Sorting) becomes optimal. Scenarios S2 and S4 involve reversals in ranking, highlighting the model's sensitivity to changes in ergonomic priorities, as shown in Table 13.

The integration of REBA and fuzzy MCDM provides a more realistic, adaptive, and responsive approach to ergonomic risk evaluation for repetitive tasks in uncertain contexts. Fuzzy TOPSIS was chosen over crisp MCDM because it can capture vagueness and allow ranking under linguistic assessments. Sensitivity analysis ensures reliability and supports decision-making under varying operational conditions, such as shift changes or worker fatigue.

Table 13
Comparison of Ergonomic Risk Assessment and Decision-Making Methods

Method	Purpose	Strengths	Limitations	Application in This Study
REBA (Rapid Entire Body Assessment)	Posture-based ergonomic risk evaluation	- Simple and widely accepted- Quantifies body posture risk- Effective for static and dynamic tasks	- Ignores task frequency and force- No integration with decision-making- Subjective scoring bias	Used as a core physical risk indicator in combination with other factors
Fuzzy Logic	Handling uncertainty and vagueness in expert evaluations	- Manages imprecise data- Flexible and human-centric- Integrates linguistic terms	- Requires expert calibration- Computationally intensive if scaled- Defuzzification needed	Used to model expert weights and task scores for REBA, repetition, and force
Fuzzy MCDM (e.g., Fuzzy TOPSIS)	Prioritize alternatives (tasks) under fuzzy multiple criteria	- Provides closeness to ideal task- Supports scenario-based analysis- Incorporates fuzzy weights and ratings	- Needs normalization and consistency- Interpretation may be complex for non-experts	Main decision engine for ranking tasks using REBA, repetition, and force inputs
Sensitivity Analysis	Assess model robustness under different weightings	- Highlights impact of each criterion- Improves transparency- Supports adaptive decision-making	- Interpretation may vary with expert opinions- Requires multiple simulations	Used to evaluate model behavior under changes in REBA, repetition, and force weights
Classical MCDM (e.g., AHP, VIKOR)	Prioritize alternatives with crisp inputs	- Easier to apply- Structurally intuitive- Well-established methodologies	- Lacks fuzziness- Less suitable for vague linguistic judgments	Not preferred due to inability to handle uncertainty in ergonomic evaluations

5. Results and Discussion

The initial REBA assessments for the three activities — Box Lifting (A1), Sorting (A2), and Labeling (A3) — indicated varying degrees of ergonomic risk caused by posture. Box Lifting registered the highest REBA values due to awkward postures and trunk bending, indicating a greater risk of musculoskeletal disorders. Labeling showed the lowest REBA values, reflecting less demanding postural requirements.

Combining REBA scores with repetition and force ergonomic factors in a fuzzy MCDM environment (Fuzzy TOPSIS) produced an overall risk ranking. Closeness coefficients identified how closely each task aligned with the ideal ergonomic condition. Using the baseline weighting scheme, Labeling (A3) emerged as the lowest-risk activity (CC = 0.616), while Box Lifting (A1) was consistently the highest-risk activity (CC = 0.366).

Sensitivity analysis under five stand-alone weighting conditions demonstrated the model's robustness and responsiveness:

i. Posture Priority (S1): Higher weighting of REBA increased the risk rating of Box Lifting, emphasizing the need for interventions in posture-intensive tasks.

ii. Repetition Priority (S2): Greater emphasis on repetition shifted the highest risk to Sorting (A2), reflecting its repetitive motion demands.
iii. Equal Weighting (S3): Outputs closely resembled the baseline, confirming model stability.
iv. Force Emphasis (S4): More physically demanding activities, such as Sorting and Labeling, showed higher risk, altering their relative rankings.

These variations underscore the importance of adaptive criteria weighting to account for dynamic work conditions and task-specific risk factors.

Integrating REBA with fuzzy MCDM enables decision-makers to effectively capture ergonomic risk in a holistic manner, considering posture, repetition, and force simultaneously under uncertain conditions. This approach facilitates proactive ergonomic risk management by:

i. Allowing dynamic weighting of criteria to reflect operational or policy changes.
ii. Providing ranked task lists for prioritized ergonomic redesign or training.
iii. Supporting worker safety through data-driven, adaptive risk assessment methods.

While the fuzzy MCDM model effectively addresses uncertainty and multiple criteria, challenges remain, including overreliance on expert judgment for weights and scoring, computational complexity for larger applications, and the need for validation with more representative task samples. Future research could explore integration with real-time sensors and deep learning for predictive ergonomic risk assessment

6. Conclusion

This study presented a dynamic ergonomic risk assessment model that integrates the Rapid Entire Body Assessment (REBA) method with fuzzy multi-criteria decision-making (MCDM) to holistically evaluate repetitive movement risks in occupational tasks. By incorporating fuzzy logic, the model can robustly handle uncertainty and linguistic imprecision commonly encountered in ergonomic assessments, providing more sensitive risk rankings based on posture, repetition, and force factors.

Sensitivity analysis demonstrated the model’s responsiveness, showing how changes in weighting priorities influence task risk rankings. This adaptability allows decision-makers to dynamically adjust ergonomic interventions according to evolving operational priorities and staffing levels.

Overall, the proposed approach offers a resilient, pragmatic, and human-centered tool for identifying and mitigating ergonomic risk factors, fostering safer work environments, and enhancing proactive occupational health management. Future research could extend this model by incorporating real-time sensor inputs and exploring the use of machine learning techniques to improve predictive capabilities.

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Conflicts of Interest

The authors declare no conflicts of interest.

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