Real-Time Ergonomic Assessment with Fuzzy Logic and RGB-D Sensors

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ABSTRACT

The integration of the Rapid Entire Body Assessment (REBA) method with fuzzy logic and RGB-D sensing technology (Kinect v1) enables greater precision and objectivity in identifying postural risks within occupational environments. This study demonstrates the effectiveness of a fuzzy system for ergonomic risk assessment in a sample of 24 workers engaged in the assembly of denim trousers. The average age of the participants from the textile sector was 27.4 years (SD ± 12.4). The proposed methodology combined the traditional REBA framework with fuzzy inference systems and real-time postural tracking via Kinect v1. Among the 24 cases assessed, 38% of workers reported no musculoskeletal discomfort, 25% reported dorsal pain, 13% experienced lower back pain, 13% reported discomfort in the neck, upper and lower limbs, and 13% also reported hand discomfort. Although statistically significant differences ($p < 0.05$) were found between the manual REBA scores and those generated by the fuzzy system, the proposed method is considered a complementary tool rather than a replacement for manual assessment. The use of Kinect as a non-invasive motion tracking device allowed for real-time data acquisition without interfering with task performance, offering a significant advantage over manual goniometric measurements, which are prone to parallax error, evaluator variability, and limitations in dynamic tasks.

Keywords-fuzzy logic; REBA method; Kinect sensor; ergonomic assessment

I. INTRODUCTION

Ergonomics is a key discipline for the prevention of Musculoskeletal Disorders (MSDs) in work environments. Ergonomic risks deteriorate the health and quality of workers' lives [1]. According to the World Health Organization statistics, more than 1.71 billion people are affected by musculoskeletal conditions globally, with low back pain being the leading cause of disability in over 160 countries. The global burden of MSDs is expected to increase due to population growth and aging, which will place greater demands on health systems and rehabilitation services. Additionally, MSDs not only restrict mobility and dexterity but also have substantial social and economic implications, such as premature retirement and decreased workforce participation [2]. MSD costs include direct expenses, such as compensation, administrative and medical expenses, indirect expenses, such as absenteeism, and losses related to quality and productivity [3].

Employee presence is vital; absenteeism directly causes measurable financial losses, reduces quality and productivity, and drives overall performance far below the organization's required productivity standards. Ergonomic intervention studies report that musculoskeletal-related absenteeism can represent between 5 % and 10 % of the total operating costs in manufacturing, while productivity losses may reach up to 20 % in repetitive-task environments [4]. These indicators emphasize the economic significance of MSD prevention and the integration of ergonomics as a strategic element of industrial management systems.

Ergonomic assessment at workstations includes observation of workers' posture and movement [5]. In this context, ergonomic assessment methods allow the identification and assessment of risk factors present in workstations, to propose redesign solutions that reduce risk to levels acceptable to the worker [6]. Ergonomic assessments quantify workstation risks; in practical applications, studies have shown that up to 60 % of operators in textile and assembly industries are exposed to high or very high ergonomic risk levels, with average Rapid Upper Limb Assessment (RULA) scores of 6–7. After redesign interventions, musculoskeletal complaints have been reduced by up to 45 %, and productivity has increased by approximately 20 % [4]. These findings reinforce the need for advanced evaluation tools capable of integrating objective and subjective parameters in ergonomic analysis.

There are several ergonomic evaluation methods whose selection depends on the specific characteristics of the activity to be evaluated, including the National Institute for Occupational Safety and Health (NIOSH) method for manual load evaluation, RULA method for postural analysis, Job Strain Index (JSI) method for the evaluation of repetitive movements, and REBA method, employed to assess the posture of the whole body [7, 8], including both the upper and lower limbs. Posture, load, type of grip, and the muscle activity developed by the worker are the factors considered in this assessment. It can also be used for the evaluation of static and dynamic postures [9, 10].

The integration of static and dynamic posture evaluation enables quantitative modelling of real work conditions. Digital motion simulation technology provides a bridge between empirical posture analysis and computational ergonomics, offering workload estimates in realistic operational environments [11]. When validated with field measurements, such simulations allow early identification of critical movements and optimization of workstation geometry to minimize ergonomic risks [12].

Digital simulations are useful for reliably assessing ergonomic risk in static postures and additional stresses, providing workload estimates in real-life tasks [13]. In this sense, expert systems are software programs that imitate human reasoning to solve specific domain problems [14], and they are utilized in fields such as engineering, social sciences, psychology, cognitive science, and human behavior [15]. Expert systems have been combined with fuzzy logic to strengthen inference mechanisms and handle uncertainty inherent to human posture evaluation. Fuzzy systems can transform linguistic variables, such as "slightly bent" or "severely twisted", into quantitative risk levels. This synergy has enabled automating large portions of ergonomic assessments and improving inter-observer consistency [16].

Fuzzy logic models play an important role in decision-making [17] and have been used to qualitatively model factors that assess occupational safety risk in the construction industry [18] or to predict fatal or minor accidents in an uncertain workplace environment [19]. A fuzzy ergonomic expert system is a technological tool that helps identify and evaluate risk factors that can lead to the development of work-related MSDs, both objectively and subjectively [20]. Reducing human error, creating expert knowledge, and interpreting a large amount of inaccurate data are characteristics of fuzzy expert systems [21]. A fuzzy expert system was designed for assessing the performance of health system factors, safety, environment, and ergonomic performance improvement at a gas refinery [21]. Also, a system based on fuzzy rules was developed to predict occupational injuries to the forearm and hand [22].

The fuzzy-based ergonomic approach can effectively predict discomfort levels and guide ergonomic redesign decisions [22, 23]. Research in manufacturing has shown that fuzzy decision systems can reduce evaluation subjectivity by 35–50 % and shorten assessment time by 40 %, while maintaining agreement with expert ergonomists [24]. This illustrates the potential of fuzzy systems as integral tools for proactive occupational-health management [25]. In [14], ergonomic deficiencies in work were related to the subjective symptoms of the worker to identify ergonomic risks of MSDs. Risk factors were grouped into main modules (symptoms, part of the compromised body) and complementary modules (work environment, work chair, work tools, organizational factors).

Similarly, fuzzy logic was used in the upper limbs to predict cumulative disorders, and thus provide the recommendations needed for the prevention of the resulting disorder [27]. Also, in [28], the ergonomic risk level of the entire body was assessed by applying fuzzy logic tools. The findings affirm that this technique avoids subjectivity during evaluation.

Complementary studies have reinforced these findings. Authors in [4] demonstrated that integrating fuzzy logic with ergonomic indicators improves the reliability of postural-risk classification and enhances the prioritization of intervention strategies. Authors in [11, 12] proved that fuzzy and value-engineering approaches increase both design efficiency and user comfort when applied to industrial tools and workstations. Such integration reduces human bias and allows continuous ergonomic improvement supported by computational reasoning.

On the other hand, Kinect technology stimulates the creation of new ideas in motion capture and virtual reality applications [29]. It is promising in assessing neurological or musculoskeletal conditions [30-32], and has proven its potential accuracy in static standing posture in a clinical setting [33]. Kinect technology has also been integrated into a real-time static ergonomic model of human surveys in an industrial environment [34]. It is considered to be a reliable range sensor that measures spatiotemporal aspects [35-37], serving as a support tool for ergonomists [38, 39].

The use of depth-sensing systems, such as Microsoft Kinect, has opened a new research line in computational ergonomics. Authors in [24] demonstrated that Kinect-based motion capture provides accurate, non-invasive postural data with an error margin below 5° for most joint angles. Its affordability and real-time capability make it especially suitable for small and medium-scale industries seeking objective ergonomic assessment. Combining fuzzy reasoning with Kinect measurements enables continuous, data-driven monitoring of workers' posture without disrupting workflow [39].

While the conventional REBA method offers a well-established framework for evaluating postural risks across multiple body segments (trunk, neck, legs, arms, wrists), it has limitations in handling risk factors such as awkward twists, lateral flexion, or sustained static postures. As highlighted in [40], while REBA and similar observational tools (RULA, JSI) are quick to apply, they often fail to incorporate subjective human variables like discomfort perception, recovery periods, or cumulative effects of repetitive movements. Integrating fuzzy logic into ergonomic assessment addresses these gaps by modeling uncertainty and human variability, thus enhancing accuracy and decision support [41]. Authors in [41] demonstrated that fuzzy inference systems using mass, exposure time, and lifting frequency can approximate ISO 11228-1 risk levels with minimal disagreement. Furthermore, studies on musculoskeletal discomfort risks [4] and ergonomic interventions in industrial settings [42] reveal the necessity of combining observational tools with advanced computational methods to capture both the objective and subjective dimensions of the risks.

This convergence between fuzzy-logic modeling and motion-capture technologies has produced a new generation of intelligent ergonomic systems. These systems transform continuous postural data into dynamic risk maps, offering real-time feedback and early-warning indicators. Comparative implementations in the textile, assembly, and food-processing sectors have reported reductions of 30 – 50 % in worker fatigue and up to 25 % improvement in task efficiency after adopting fuzzy-REBA monitoring frameworks [22, 24]. Such outcomes demonstrate not only practical gains but also theoretical advancement in ergonomic evaluation through the integration of computational intelligence and biomechanics.

Research also highlights the growing importance of motion capture technologies in ergonomics. Authors in [24] reviewed motion capture for ergonomic assessment, emphasizing its ability to deliver real-time, objective, and non-invasive postural data, significantly reducing observer bias and enhancing reproducibility compared to traditional methods. Comparative studies have shown that Kinect-based motion capture, in particular, provides an accessible yet sufficiently accurate solution for field applications, aligning well with ergonomic assessment requirements [24, 43]. By enabling automatic acquisition of body angles and movement trajectories, Kinect overcomes the subjectivity inherent in observational scoring. Therefore, the proposed approach, which integrates REBA with fuzzy logic and Kinect-based data acquisition, offers a more comprehensive, reliable, and effective worker assessment method. It leverages the structural strengths of REBA in evaluating whole-body posture while extending its analytical power through the fuzzy modeling of uncertainty and objective motion capture inputs.

The current study focuses on designing a fuzzy system to ergonomically evaluate real-time workstations using a natural user interface (Kinect v1) and REBA. Furthermore, it assesses the effectiveness of the fuzzy expert system of 24 workers in a textile industry to identify the level of ergonomic risk to which workers are exposed.

Beyond methodological validation, the impact of this experimental study lies in demonstrating how a fuzzy-REBA–Kinect framework can be generalized for regional application in labor-intensive sectors. If adopted throughout industrial clusters, projections suggest a 40 % reduction in reported fatigue symptoms and a 20–30 % rise in sustained productivity, aligning with international occupational-health benchmarks. The findings, thus, contribute simultaneously to ergonomic science by advancing hybrid computational models and to socio-economic development, by enabling safer and more efficient workplaces within emerging economies.

II. MATERIALS AND METHODS

The experiments involved in this study were carried out in the textile industry employing a fuzzy system, along with a natural user interface, to determine the level of ergonomic risk using the REBA method. Furthermore, a Mamdani-type fuzzy inference system was implemented, as it models ergonomic risk factors utilizing linguistic rules that closely resemble expert reasoning. Unlike the Sugeno or Tsukamoto approaches, which rely on functional outputs and are more suitable for optimization or control applications, the Mamdani method allows ergonomic experts to easily interpret rules such as "if the load is high and the exposure time is long, then the risk is very high." This interpretability makes it particularly appropriate for applications in occupational health and ergonomics.

A. Participants

The experimental data were obtained from the denim trouser assembly line of a textile company located in the state of Hidalgo, Mexico, whose manufacturing system has eight workstations. Twenty-four participants with an average age of 27.4 (± 12.4) years were included in the study. All participants performed repetitive tasks, maintained prolonged postures, and had at least six months of work experience. This specific sample size resulted from the application of strict inclusion and exclusion criteria to ensure data consistency and reliability. Workers undergoing medical treatment for musculoskeletal injuries were excluded to avoid confounding factors that could bias the ergonomic risk assessment. Although the final cohort is limited in number, it represents a homogeneous group aligned with the study's objectives, allowing for controlled evaluation of the fuzzy-Kinect-REBA system under defined ergonomic risk conditions. All participants gave informed consent.

B. Measurement Protocol

Angular data acquisition was performed using the Kinect v1 sensor, which allowed real-time recording of the joint angles of the trunk, neck, arms, and legs during the execution of the tasks. The analysis was carried out in an assembly line composed of eight workstations, each with specific functions within the textile production process (cutting, front sewing, back sewing, assembly, final sewing, ironing, inspection, and fusing). Workers were evaluated at their usual station during their normal working day, without any interruption of the production flow.

The assembly of the jeans starts with the "cutting" workstation, which performs seam cutting, over-threading, fastener preparation, viewing, bag stitching, and locking. In the "front sewing", cuts are made in front of the jeans, closures, bags are attached to the panels, and bag-highlighting is done. The "inspection" workstation checks the quality of the cuts and the pieces of the jeans are formed, in addition to marking the points to secure rear bags. At the "ironing" station, the rear bags are ironed. The "fusion" station is used when jeans require double fabric in the bags. The front and back of the jeans are taken to the "assembly" workstation. In this station, the stitching is made, and the sides, the crotch part, the tip, frame, and wheel are closed. In the "final sewing" station, operations, such as over-spinning, buttonhole, gluing lock, clips, and button placement, are performed. Finally, the finished garments are transported to the storage area.

C. Fuzzy System

Based on the REBA method proposed in [10], a fuzzy model was formulated for ergonomic risk assessment at workstations, which integrates inputs, processes, and an output.

1) Input

The input considers the measurement of the angles of the body parts of group A (trunk, neck, legs) and group B (arm, forearm, wrist), which are obtained in real-time with the Kinect v1 sensor.

2) Process

The model consists of three fuzzy systems, as shown in Figure 1. The first assesses group A (trunk, neck, and legs) and their corrective factors, and the second obtains the assessment of group B (arm, forearm, and wrist) and its corrective factors. In the third system, the combination of groups A and B is valued.

The first fuzzy system obtains the assessment of group A (trunk, neck, and legs) and its corrective factors, such as trunk twisting, lateral bending of the trunk, neck rotation, and leg instability. Inference and defuzzification are represented by 60 inference rules with scores between 1 and 9, where one or more rules can be activated (with or without a corrected score) according to their membership grades between contiguous levels, so as to get the final defuzzification score deploying the singleton method. The correction factor is then applied according to the weight of the burden (0, +1, +2), and +1 point if force is applied abruptly.

The second system defines the fuzzy sets of the arm, forearm, and wrist. When combined, they produce 36 inference rules, each assigned a score from 0 to 9. The singleton method is used for inference and defuzzification, and the Group B score is increased according to the grip type (0, +1, +2, +3). The third diffuse system is used for the estimated evaluation of musculoskeletal risk. It receives the outputs of groups A and B ratings as input and combines 144 inference rules with scores assigned between 1 and 12. Assigned scores may increase due to muscle activity.

3) Output

The output is shown in the form worker's ergonomic risk in five levels: imperceptible, low, medium, high, and very high.

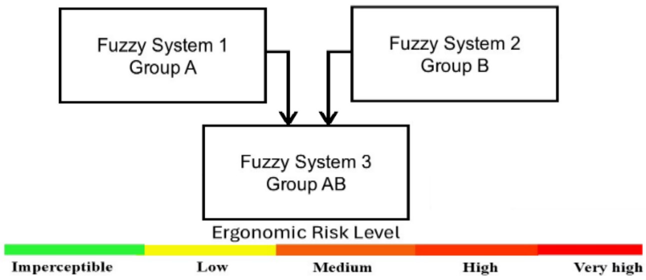

Fig. 1. Fuzzy system.

D. Experimental Stage

An Acer Intel® Core™ i7-7500U 2.70 GHz laptop computer with Intel® HD graphics card was used to perform the ergonomic assessments. At this stage, calibration tests were performed for angular data acquisition. For instance, the angles obtained by the Kinect v1 sensor were manually compared with a goniometer, as depicted in Figure 2. As previously reported, the difference between manual and Kinect v1 assessments varies between ±5°.

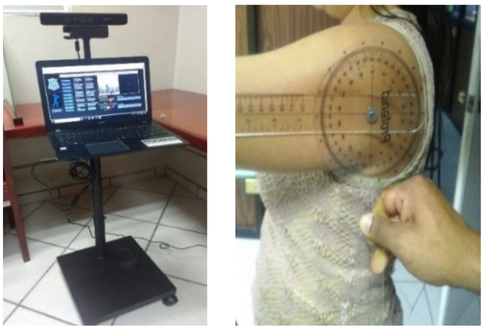

Fig. 2. Fuzzy system versus goniometer data.

The joints selected by the Kinect are portrayed in Table I.

TABLE I. JOINTS USED BY REBA METHOD

Group	Angles	Joints
A	Trunk	Spine base, spine mid, spine shoulder
	Neck	Spine, shoulder, neck, head
	Legs	Knee, ankle, hip
B	Arm	Shoulder, elbow, spine
	Forearm	Elbow, wrist, shoulder
	Wrist	Wrist, hand, elbow

The angles of each segment of the body vary among workers, as it depends on the type of the activity they perform in their work area at the time of angular valuation. The acquisition of these angles is important, since they provide the guideline for the application of the fuzzy model with the REBA method.

Equation (1) was used to measure the angles of groups A and B using the REBA method:

$$\theta = cos^{-1}\frac{v.w}{|v||w|} \quad (1)$$

where θ corresponds to the inverse cosine of the point product of the vector v and w.

The semi-automated system allows the assessor to select the left or right side to be assessed and the parameters of trunk torsion, neck torsion, repetitive movements, load, unstable postures, and sharply applied forces. These parameters were observed and entered manually by the assessor during the execution of the workers' activities.

III. RESULTS

Due to the nature of the data, the Wilcoxon non-parametric test was applied to compare the differences in ergonomic risk levels between the manual REBA methodology and the REBA methodology included in the fuzzy expert system. The statistical analysis was conducted in MATLAB (R2017b, MathWorks, Natick, MA, USA), using the risk level data obtained from both the conventional REBA method and the fuzzy expert system.

According to Table II, on average, each fuzzy score is within ±1.17 points of the entire manual REBA assessment. Also, a Root Mean Square Error (RMSE) of 1.58 represents differences of 2-3 points between manual and fuzzy assessments. Regarding the correlation (Pearson's $r \approx 0.66$), there is a moderate to strong and significant correlation (p <0.05). When the manual score increases, the fuzzy score also tends to increase, although not continuously. On the other hand, the Wilcoxon test indicates significant differences (p <0.05). For example, there is a systematic bias, according to the type of activity performed at different stages of the jeans-making process. In several postures, the score is higher (or lower) than that obtained manually.

TABLE II. RESULTS OBTAINED FROM ERGONOMIC EVALUATION

Workstation	Worker	REBA method		Fuzzy expert system	
		Score	Risk	Score	Risk
Preparation	1	4	Middle	4	Middle
	2	6	Middle	6	Middle
	3	6	Middle	6	Middle
Front	4	8	High	9	High
	5	8	High	8	High
	6	8	High	6	Middle
	7	8	High	8	High
	8	9	High	9	High
	9	9	High	8	High
	10	8	High	8	High
Rear	11	8	High	9	High
	12	8	High	10	High
	13	8	High	10	High
Assembly	14	8	High	10	High
	15	7	Middle	8	High
	16	7	Middle	9	High
	17	7	Middle	9	High
Finished	18	7	Middle	6	Middle
	19	7	Middle	10	High
	20	11	Very High	12	Very High
Ironing	21	6	Middle	6	Middle
Review	22	7	Middle	6	Middle
Finished	23	8	High	10	High
	24	5	Middle	9	High
Pearson's r	0.66				
Mean Absolute Error (MAE)	1.17				
RMSE	1.58				

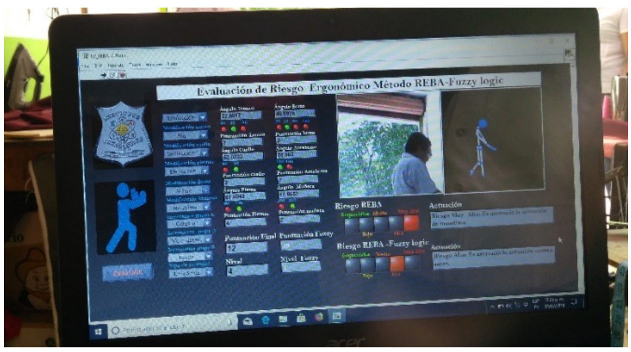

Fig. 3. Control panel: REBA versus REBA fuzzy logic.

In Figure 3, a participant is shown at their workstation. The sensor Kinect was positioned on a stable base at a height of 80 cm and at a distance of 2 m from the participant. The control panel displays the risk levels obtained through both the conventional REBA method and the fuzzy REBA approach.

The traditional REBA assessment indicates a high-risk level, whereas using the same angular measurements, the fuzzy REBA method classifies the risk as very high. This discrepancy arises because fuzzy logic can anticipate gradual changes in risk levels through the combination of expert-validated inference rules, while the conventional REBA method relies on fixed scales that do not capture progressive variations across different risk categories. As presented in Figure 4, when applying the traditional REBA method, the level of risk ranges from medium to high, with only one case of risk considered to be very high. On the other hand, when applying the fuzzy model, more accurate scores are obtained since fractional regions in the score are considered according to the fuzzy rules. This results in 19 cases of high ergonomic risk, 4 cases of medium risk, and a single case of low risk for developing MSD.

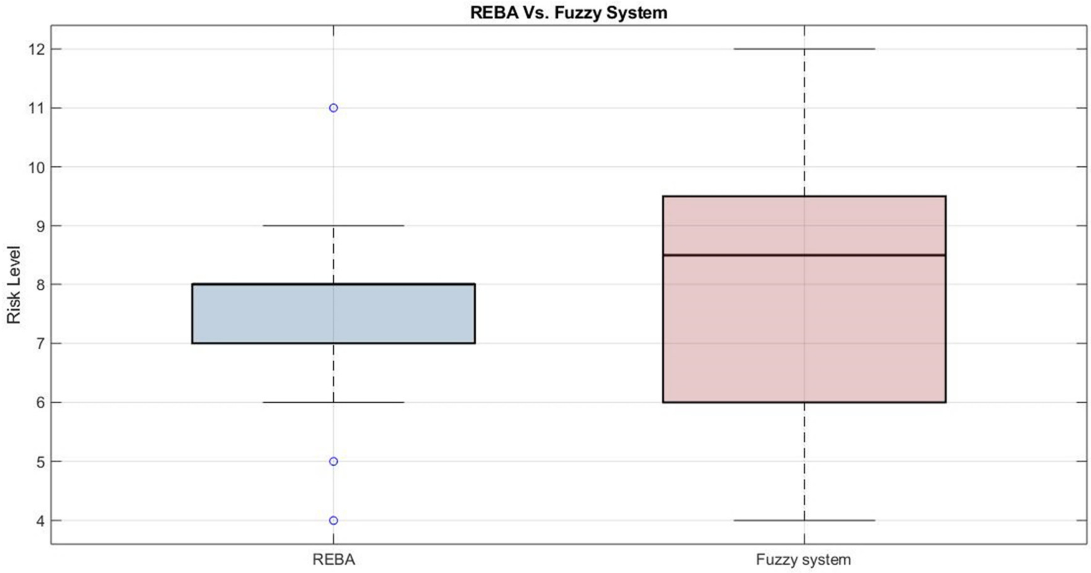

Fig. 4. REBA versus REBA fuzzy logic method.

IV. DISCUSSION

The risk of work-related MSDs is one of the most serious problems in the industry, regardless of the sector in which the work is carried out, such as agriculture or mining [44], where all workers are exposed to musculoskeletal injuries. This study deals with the workers of the jeans manufacturing assembly and their workload of repetitive activities and burden manipulation. Their work requires being in a static position involving the upper and lower limbs throughout the working day. These activities can increase ergonomic risk and, depending on the level of exposure, may lead to MSDs.

This study developed an ergonomic assessment system based on the REBA method adapted to fuzzy logic, and employing Kinect v1 depth sensors for postural data acquisition. According to the real-time ergonomic risk analysis with the fuzzy system, the study evaluated 24 cases, of which 19 workers showed a high risk of developing MSDs, 4 a medium risk, and 1 a low risk. 38% of the workers did not report any musculoskeletal discomfort, 25% reported dorsalgia, 13% lumbalgia, 13% discomfort in the neck and upper and lower limbs, and 13% hand discomfort. The results displayed a moderate correlation between the traditional manual method and the fuzzy approach (Pearson's $r \approx 0.66$), indicating that although the scores are not identical, both methodologies tend to follow a similar pattern of variation.

However, the Wilcoxon signed-rank test revealed a statistically significant systematic bias ($p < 0.05$), suggesting that the fuzzy system consistently overestimates or underestimates values in comparison to the manual method. Moreover, the MAE of 1.17 and RMSE indicate an average deviation of more than one point between both approaches. In this study, systematic bias refers to a consistent and predictable deviation that arises when comparing the outcomes produced by the fuzzy REBA system with those of the conventional REBA method. This phenomenon stems from the inherent nature of the fuzzy approach, which employs gradual transitions and degrees of membership rather than the discrete thresholds that define the original REBA scale. Although these differences are often subtle, even a minimal deviation may lead to a change in risk classification, for instance, shifting an assessment from medium to high with direct implications for the prioritization of preventive measures and ergonomic decision-making. Recognizing the presence of this bias highlights the need to consider the fuzzy REBA a complementary tool, offering enhanced sensitivity and interpretative nuance, but not a substitute for the validated standard method. As noted in [4, 11, 12, 19-27, 41], fuzzy models can serve as technological tools for objective evaluation and decision-making support.

In the context of a textile industry characterized by open workspaces, variable postures, and repetitive cycles, the use of Kinect as a non-invasive postural tracking tool allows real-time data capture without interfering with task performance. This presents a significant advantage over manual goniometric measurements, which are subject to parallax errors, evaluator variability, and limitations in dynamic tasks. Additionally, fuzzy logic enables a continuous interpretation of ergonomic risk, capturing subtle postural changes that might be overlooked in discrete scale assessments. These findings align with [22, 37, 38, 42], where it is indicated that the Kinect v1 sensor is a non-invasive device utilized in ergonomic risk assessment, with an error margin of up to ±5°. As a result, using the Kinect v1 sensor alongside the REBA method, integrated into a fuzzy system, enhances the latter's analytical capabilities making it a comprehensive, reliable, and effective tool for assessment.

Nonetheless, due to the identified systematic bias and the potential implications of single-point differences in risk classification (e.g., transitioning from "medium" to "high" risk), it is proposed that the fuzzy system be used as a complementary tool, rather than as a substitute.

In this experimental study, both ergonomic and environmental conditions were not optimal, as observed while performing the real-time ergonomic risk assessment. The study proposes establishing rest intervals since activities are repetitive and workers remain seated for long hours, changing wooden seats for comfortable ones, as well as comfortable shoes and anti-fatigue mats.

V. CONCLUSIONS

The integration of fuzzy logic, Rapid Entire Body Assessment (REBA), and Kinect achieved a 66% correlation with conventional REBA scores, explaining 43.6% of the variance. The system recorded a Mean Absolute Error (MAE) equivalent to only 7.8% of the REBA scale and a Root Mean Square Error (RMSE) of 10.5%. These results confirm that the proposed approach maintains high reliability while reducing observer subjectivity, thereby providing a practical and accurate tool for real-time ergonomic risk assessment.

The study offers practical insights for industries with high exposure to Musculoskeletal Disorders (MSDs). A validated fuzzy-Kinect-REBA system could serve as a low-cost and non-intrusive monitoring tool, enabling managers to continuously track worker posture and intervene before injuries occur. Given that the system demonstrated reliable agreement with manual REBA scores (r = 0.66, MAE = 7.8%, RMSE = 10.5%), its adoption may contribute to measurable organizational outcomes, such as reductions in MSD-related absenteeism (previous studies report reductions ranging from 20% to 80% in intensive ergonomic intervention settings), depending on the scale and fidelity of implementation and improved productivity through healthier workforces [45]. For policymakers, the research also provides a foundation to propose technology-assisted ergonomic risk assessments as part of occupational health standards.

While the present study demonstrates the feasibility of integrating fuzzy logic, REBA, and Kinect for real-time ergonomic risk assessment, several avenues for future research remain open. Testing with newer Kinect versions (e.g., Azure Kinect) is particularly relevant, given their improved depth accuracy and skeletal tracking capabilities. Beyond sensor improvements, subsequent studies should aim to (i) expand the sample size by including more than 100 workers across multiple industrial sectors to strengthen the generalizability of the findings, (ii) benchmark the fuzzy-REBA-Kinect framework against alternative motion capture systems, such as Opti Track, Vicon, or IMU-based wearables, to better understand cost-effectiveness and accuracy trade-offs, (iii) explore hybrid models that integrate machine learning techniques alongside fuzzy logic to enhance categorical precision in risk level prediction, and (iv) assess the longitudinal impact of technology-assisted ergonomic monitoring on both injury reduction rates and organizational productivity, ideally through 6–12 month interventions, tracking MSD incidence and absenteeism.

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