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Article

An Integrated and Validated Ergonomic Risk Assessment Framework for the Construction Industry

Robin V John Fernandes[1], S.M Tauseef[2], N.A Siddiqui[3]

[1,2]UPES Dehradun, Uttarakhand 248007
[3]GD Goenka University, Haryana 122103
Email: fernandesrobin.28@gmail.com*

Abstract: The construction industry is among the most hazardous occupational sectors, with workers frequently exposed to musculoskeletal disorders (MSDs) due to heavy manual tasks, awkward postures, and repetitive movements. Globally, work-related MSDs affect more than 1.7 billion people, while studies in India report MSD prevalence among construction workers ranging between 55% and 70%, highlighting the severity of the problem in labour-intensive construction environments. In India, where construction remains largely labour-intensive and ergonomics is often overlooked, the need for systematic and validated risk assessment is critical. This study proposes a standardized ergonomic assessment methodology that integrates observational tools—Workplace Ergonomic Risk Assessment (WERA) and Rapid Entire Body Assessment (REBA)—with worker-reported MSD outcomes. Unlike many previous studies that relied exclusively on self-reported questionnaires or single observational assessments, this dual-framework approach combines objective posture evaluation with worker feedback to improve assessment validity, reliability, and applicability across construction settings. The findings reveal job-specific ergonomic risk profiles, with plumbers and electricians exhibiting the highest MSD prevalence, confirming the practical value of integrating posture analysis, ergonomic scoring, and self-reported outcomes. Beyond identifying high-risk roles, the methodology provides actionable, data-driven insights for task redesign, rotation scheduling, targeted training programs, and ergonomic risk-factor mitigation. The inclusion of quantitative validation using ergonomic risk scores and predictive analysis further differentiates this study from purely descriptive ergonomic assessments. By bridging observational data with worker-reported outcomes, this research contributes a replicable, scalable, and context-sensitive ergonomic framework capable of supporting proactive safety interventions, strengthening safety culture, and enhancing productivity in the construction industry.

Keywords: Safety culture; Safety performance; Ergonomics; Musculoskeletal disorders; Construction risk assessment.

1. Background

The necessity to decrease ergonomic risk and musculoskeletal diseases (MSDs) in construction occupations, notably in India, drove this concept. Construction is one of the most dangerous occupations worldwide, and Indian workers endure long hours of manual labour, awkward body postures, repeated movements, and heavy manual material transportation [1]. The nature of this work increases the likelihood of MSDs and can threaten the health of workers as well as productivity and project completion timeframes, ultimately impacting the bottom line. Though substantial, extensive, systematic research addressing these issues has primarily been scant [2]. This research introduces a standardised and scientifically validated strategy that uses observational tools—WERA and REBA—to provide worker self-reported MSD outcomes. Previous approaches to combining MSD risk assessment were often fragmented by relying on self-report MSD measures or only using observational ergonomic measures; this strategy demonstrated balance to improve comprehensive ergonomic risk assessment by combining objective posture scoring with workers' self-reported health outcomes; allowing for identification of occupations, tasks, and demographic factors most likely to increase MSD risks among construction occupations [3].

The primary motivation of this research is to promote a proactive safety culture in construction, where ergonomic risk factors are addressed alongside traditional accident prevention measures [4]. By emphasizing ergonomics, organizations can address not just reactive safety approaches, but truly proactive strategies that aim to prevent chronic health concerns. The standardized methodology developed in this investigation generates important indicators for managers, policymakers, and ergonomists to influence the design of fluid interventions, including ergonomics equipment, design tasks for rotation, and training programs. The other motivation for this methodology is the relative ease of use, repeatability, and adaptability [5]. The use of a structured approach to collecting data, involving direct observations, validated scoring systems, and interviews with the workers, offers a high degree of accuracy and reliability in validity. The validation—cross-checking posture scores against MSD prevalence, and re-validating data—imparts robustness to the methodology. This way, it is not only applicable to the site that was studied, but could also be adapted to various construction settings in India or similar labor-intensive industries [6]. Ultimately, the motivation behind this methodology is twofold: promotion of well-being for workers and promotion of operating efficiency for organizations. By reducing the prevalence of MSDs, construction organizations can reduce absenteeism, compensation costs, and ultimately productivity, whilst in parallel construction of a safer and necessary role for sustainability of workplace conditions. In doing so, this methodology provides a contribution to the long-term ambition of mainstreaming ergonomics into occupational safety infrastructure, in turn promoting the health of the worker as well as performance within the industry [7].

Ergonomics Interventions and Safety Culture in the Construction Industry

Everyone in the construction industry cares most about the health and safety of their workers. It is mandated by law and morally sound to safeguard the health and safety of workers. Additionally, it is significant for the construction industry achievement and reputation [8]. People who work in the **construction industry** have to deal with a lot of problems, like having to work at heights, lift heavy things by hand, use complicated tools, and perform labour-intensive tasks. Work-related injuries like musculoskeletal disorders (MSDs), accidents, and other harm are more likely to happen because of these issues. There are many ways to lower these risks, though. The construction industry, for instance, could make the workplace safer and better for everyone by using ergonomic tools and following ergonomic procedures [9]. Maintaining safety is the most important part of working in the construction industry. Bodily harm at work can not only affect the health of the workers, but also the business's money, reputation, and ability to complete tasks. Building companies can show they care about the safety of their employees by promoting a good safety mindset [10]. As a result, workers are more likely to put safety first every day at work. Ergonomic considerations such as hydraulic lifts, electric drills, ergonomic office-style chairs, and other lifting supports will aid construction organizations in decreasing physical labor for workers, supporting a healthy posture, and reducing the chances of repeated stress injury and various MSD [11]. Furthermore, workers are safer and more productive than ever before—workers can often concentrate solely on their work without distraction. However, precautionary measures for ergonomic on-site concerns necessitate proper training and education. Workers must be knowledgeable about the significance of evaluating ergonomic protocols and equipped with knowledge of how to use the tools available to them correctly. The focus of educational experiences should include safe lifting techniques, awareness of posture, and the appropriate use of ergonomic equipment [12].

Figure 1. Typical ergonomic and occupational hazards observed at a construction site, including awkward postures, manual material handling, and repetitive tasks [9]

Figure 1 illustrates common ergonomic risk exposures and occupational hazards frequently observed at construction sites. To promote the use of ergonomic risk factors and build a solid safety culture, it is important to keep everyone aware and engaged. Through safety meetings, bag talks, and safety groups, management and workers can talk about safety issues and come up with ways to make the workplace safer on a regular basis. When workers have a reason to make the workplace safer, they are more likely to take responsibility for it and work together to make it safer [13]. Ergonomic practices can only continue to be effective if the practices are watched regularly and evaluated. Regular assessments, audits, and feedback mechanisms offer organizations the opportunity to identify issues, receive input from employees, and implement corrective actions. By taking these actions, construction organizations can improve their ergonomic policies and procedures, adapt to changing conditions on the job, and leverage technology developments again to improve safety for their workers [14].

To protect workers and improve long-term benefits, the construction industry needs to use optimal risk factors and methods and improve the general safety mindset for workers. Construction firms can create an environment of work that encourages worker safety, improves productivity, and improves their overall image by recognizing ergonomic risk factors and mitigating associated risks, choosing ergonomically appropriate tools, providing robust and reasonable and continuous education, communication, and engagement, with ongoing monitoring and evaluations of practices frequency of incidents, evaluating incidents, and recognizing and rewarding safety as a behavior in the workplace reinforcement plan [15].

Importance of improving safety culture in the construction industry

Safety culture serves a purpose beyond compliance; it affects the reputation of the organization, as well as its long-term sustainability. Research in the Indian context has shown prioritizing safety helps improve employee engagement and reduces risks for chronic health issues, especially in labor-intensive settings such as construction [18]. When safety is a top priority (and management is involved), it builds trust between management and workers, making it easier for workers to report dangers and make recommended design changes.

Improving safety culture goes beyond a reduction in accidents; it contributes to resilient, productive, and health-oriented organizations. To find out how these two things can be combined to make construction sites safer, this study looks at physical assessment tools and organised decision-making methods.

Ergonomic Tools to enhance safety culture

Ergonomic tools play a vital role in reinforcing safety culture by minimizing physical demands on workers, improving task design, and increasing confidence in organizational safety measures. These tools deal with fatigue, awkward postures, and repeated movements to mitigate risks of musculoskeletal disorders (MSDs) while also increasing productivity and satisfaction [19]. Mechanical tools, ergonomic workstations, and structured assessment methods like the Workplace Ergonomic Risk Assessment (WERA) and the Rapid Entire Body Assessment (REBA) are all examples of ergonomic interventions. These help figure out risk levels and give standardised scores to risks related to posture work. Checklists are no longer the only way to do assessments. Wearable sensors, surface electromyography (sEMG), and machine learning techniques can now be used to get a better idea of physical load and risk in real time[20]. With these changes, we are moving from controlling dangers reactive hazard control to measuring hazards before they happen using data. Using ergonomic tools in construction sites as part of safety culture programs will help make sure workers are safe and healthy on the job while still meeting efficiency goals. This study carries the topic of understanding ergonomic risk by providing worker-reported outcomes related to the use of WERA and REBA while using advanced ranking methods to ensure an integrated and easily replicable approach to ergonomic risk management in labor-intensive environments.

2. Related Work

This section reviews existing research on improving safety culture in the construction industry through ergonomic risk assessment and related analytical approaches.

Alkaisy et al [21] proposed the use of machine learning models predict the occurrence of construction-related incidents. They used the 16,878 records of accidents that happened on Australian construction sites to train machine-learning models. Decision Tree (DT), K-Nearest Neighbour (KNN), and Dynamic Time Warping (DTW) were the machine learning models that were used to find risks in the workplace. Random Forest (RF) achieved an accuracy of 89.3%. While traditional safety culture development models focus on organizational practices, recent studies increasingly employ machine learning techniques to enhance task-level risk prediction. These methods add to safety culture models by giving data-driven ways to measure risks linked to position. The goal of this study is to come up with a growth model that can be used to measure and encourage a strong safety environment in the building business. The model that was made was tested using the Delphi method. The model describes five steps of development that can be used to judge how strong a building company's safety culture is. It talks about 19 things that make safety settings resilient at different stages of growth.

Lastly, it was decided that the suggested model lets companies see how mature their current adaptable safety environment is and figure out what they need to do to get to a higher level of development. According to Tappura et al. [23], safety culture is a big factor in how well safety works. There aren't many studies, though, that look at how to start a safety culture in a company or how worker happiness is related to how mature a safety culture is. Tappura et al. [23] looked at how happiness of workers in a company changed as different parts of the safety culture got better. PLS-SEM and group comparisons were used to analyze the data. The biggest factor in how happy workers were with the safety culture was found to be their dedication to it. The findings indicated that mature communication can explicitly encourage employee commitment.

Mudiyanselage et al., [24] demonstrated that manual resource handling duties can be quite hazardous from an ergonomic standpoint. Material handling ergonomic risks can be reduced using safety inspections that monitor body positions. This study assesses the effectiveness of devices based on ground Electromyogram (EMG) in combination with machine learning (ML) methodologies to recognize body movements which may lead to muscular injury due to substance handling autonomously. Four different ML approaches have been developed - Decision Tree (DT), K-Nearest Neighbor (KNN), and Random Forest (RF). Risk assessment scores were assigned based upon the lifting equation to classify. According to the current study, DT models can predict the overall risk with precision that approaches 99.35%.

Fernandez et al., [25] created a method that utilizes computer vision and ML algorithms for automatically calculating Rapid Upper Limb Assessment (RULA) values from photographs or digital video to provide an accurate ergonomic risk assessment. This method provides a solution to limitations in recent advancements that only use computer vision or wearable assessment tools and may be ultimately capable of participating in unsupervised evaluation and assessing many workers at one time. This is possible because the system can watch many people safely at the same time. Open-source neural systems are used in the processing processes to find the bodies of the workers. After that, the places and angles of their body joints are figured out, and RULA scores are made using this data. A strong correlation was observed between the predicted RULA scores and expert evaluations reported in the study. In most of the real-world tests, the Cohen's coefficient was over 0.61.

A study by Deros [26] showed that one of the primary causes of work-related musculoskeletal injuries is due to they don't do the basic moves needed for material handling correctly. This could cause big problems with the joint system. The study's results give us a way to figure out how much motion the lifter is experiencing while workers involved in manual material handling tasks. The lifting task outcomes were analyzed using Snook's Table to quantify acceptable load limits based on task conditions. The data that were collected are evaluated using a technique called Dynamic Time Warping (DTW), which compares the motion sequences of two different videos to find out which one is more comparable. In the end, it was determined that the findings of their study demonstrated have the potential to impact and contribute to the manual material handling business.

Kulkarni and Devalkar [27] found that overworking the body and doing the same things over and over again can cause many injuries, stresses, and strains. The study aimed to evaluate the biomechanical demands associated with different construction tasks. Finding out how common joint diseases are and what can be done to avoid them is another goal of the study. For the study, the RULA and Rapid Entire Body Assessment (REBA) tests are used to analyse the posture of construction workers doing various tasks. RULA and REBA-based assessments revealed that workers were most likely to get Cumulative Trauma Disorders (CTDs) in their shoulders, knees, legs, and back because of the abduct or lower body position.

Brandt et al. [28] agreed that construction work involves high physical workload demands and that reducing work that is hard on the body is a top goal. Using surface Electromyography (sEMG), muscle activity was quantitatively monitored to assess physical workload. Therefore, awareness of these occurrences could be useful in reducing risks associated with the workplace. The findings indicated no significant reduction in occurrences involving excessive physical workload. Participatory Ergonomics (PE) has demonstrated some potentially beneficial effects, but it is not yet clear whether or not it can be implemented as a strategy to lessen the amount of physical labor required for building work.

Valero et al., [29] observed that human body movements have been studied for decades to improve the well-being of workers in the workplace as well as their performance in their jobs. The ongoing development of small wearable sensors has the potential to completely transform biomechanical analysis by delivering precise and up-to-date information on quantitative motion in real-time. After that, a variety of techniques for assessing working positions and motions are analyzed and contrasted, with an emphasis placed on highlighting the technological advancements, restrictions, and voids. It gives us a new way to find and describe building workers' dangerous positions. This system is all about getting moving data from portable Inertial Measurement Units (IMUs) that are worn and connected to a body area network. In the end, the results showed that the suggested model is more accurate and reliable than the old ways of doing things that were used before.

Ajayi et al., [30] highlighted that construction is typically perceived to be a fragmented business, and that integration and coordination across various processes and parties are considered to be the approaches to resolving the challenges generated by the fragmentation on the safety and health of construction workers. Construction workers exhibit a higher incidence rate of work-related musculoskeletal disorders, which results in days absent from work and affects the rate of productivity. People with these illnesses have to miss work. The study employed both a literature review and a structured questionnaire to come up with the proposed combined structure. People who work in building can use this organised, systemic method to make their jobs less stressful when they have Work-Related Musculoskeletal Disorders (WMDs). This is done so that there is a way to lessen the effects of WMDs on construction sites. To make the operating network of workplace ergonomics between construction workers as efficient as possible and to promote safe work habits in creating, which was proposed as a strategy to reduce the prevalence of WMDs in the construction industry. Sagar et al., [31] observed that female workers are not given the appropriate load to carry following their physical characteristics and levels of strength. This results in an uneven allocation of work within construction companies, which in turn leads to serious physical backache problems for the employees, and a decrease in the weightlifting strength of women workers. The purpose of their study demonstrated is to effectively determine the optimal pairing of three parameters (worker age, worker weight, and worker strength) for mitigating the load constant of the women worker. In order to do this, the study used the Taguchi Parameter Optimization (TPO) method. Ultimately, mathematical modeling was applied to determine, it was determined that one can select the proper load for a given operation to minimize the risk of women workers in the construction company developing back aches.

Existing ergonomic assessment approaches vary widely in scope and applicability. Traditional tools such as WERA and REBA provide structured observational scoring but often fall short in capturing cumulative risks and subtle biomechanical variations. RULA, while effective for upper-limb postures, has limited generalizability to whole-body tasks common in construction work. Recent advances with wearable sensors and computer vision-based models offer real-time, quantitative insights, yet their deployment in resource-constrained construction environments remains challenging due to cost, technical expertise, and site variability. Machine learning models, such as Random Forest and sEMG-based classifiers, show promising accuracy in detecting high-risk movements, but most validation has been done in controlled laboratory settings outside India. Compared to these fragmented approaches, the present study contributes by integrating validated observational tools with worker-reported outcomes to create a replicable, low-cost, and context-sensitive methodology tailored to Indian construction sites, addressing the current literature gap in scalable ergonomic risk assessment.

Table 1. Comparison of Tools

Tool/Approach	Advantages	Limitations	Applicability in Indian Construction
WERA (Workplace Ergonomic Risk Assessment)	Quick, covers posture, force, repetition, and duration	Limited predictive accuracy (AUC ~0.56); observer-dependent	Feasible, low cost; suitable for large, labor-intensive sites
REBA (Rapid Entire Body Assessment)	Captures whole-body posture risks; widely validated	Poor standalone predictive power; snapshot-based	Useful but may miss cumulative exposures in dynamic tasks
RULA (Rapid Upper Limb Assessment)	Focused on upper limb strain, simple scoring	Narrow scope; ignores lower body and whole-body risk	Limited in Indian context where tasks involve full-body exertion
Wearable Sensors (IMUs, sEMG)	Provides continuous, real-time data; high accuracy	High cost, training required; data processing challenges	Limited use in Indian construction due to affordability and adoption barriers
ML/AI Models (RF, CV-based RULA, DTW, etc.)	High classification accuracy (up to 99% in lab tests); automated	Requires large datasets, may lack field validation	Potential for future integration, but currently impractical at site level

3. Method Details

Study Design and Location

A cross-sectional observational study was conducted at a single construction company site in India. The site was selected based on its large workforce and diversity of job roles, ensuring representative data across multiple trades.

Sample Size and Selection

A total of **700 workers** were surveyed and observed. Inclusion criteria included active employment at the site for at least six months. Workers from different job types (supervisors, electricians, carpenters, masons, etc.) were included to capture variation in ergonomic risk exposure.

Data Collection Procedure

1. **Demographic and Anthropometric Data**
    - Age, experience in years, and BMI were recorded through interviews and physical measurements.
2. **Work Profile Assessment**
    - Job type and average daily work hours were documented.
3. **Ergonomic Risk Assessment**
    - **Posture Score**: Assessed through direct observation of working postures during typical tasks.
    - **WERA (Workplace Ergonomic Risk Assessment)**: Applied to evaluate risk based on posture, force, repetition, and task duration.
    - **REBA (Rapid Entire Body Assessment)**: Used to assess whole-body postural risks.
4. **Musculoskeletal Disorder (MSD) Screening**
    - Workers were asked about MSD symptoms (Yes/No) using a standardized questionnaire based on Nordic Musculoskeletal Questionnaire guidelines.

Data Recording and Tools

- Observations were recorded on structured data sheets.
- Measurements were taken using standardized instruments (digital weighing scale, height measuring tape).
- Ergonomic risk scores (WERA, REBA) were computed using established scoring systems.

Ethical Considerations

- Informed consent was obtained from all participants.
- Data confidentiality was maintained.

Data Analysis

The collected information was digitised and analysed using descriptive statistics and correlation analysis to examine associations between workplace risk factors and the prevalence of musculoskeletal disorders (MSDs).

Sample Size Justification

The sample size of 700 construction workers was selected to ensure statistical reliability and adequate representation of diverse job roles within the study site. The justification is threefold:

1. **Prevalence-Based Estimation:** Earlier research on musculoskeletal disorders in construction workers has shown prevalence rates between 50-70% (Chellappa et al., 2021; Ajayi et al., 2015). A confidence level of 95% and an error range of +/- 5% were used to figure out the smallest sample amount that was needed. The maximum expected MSD prevalence was set at 50% was set at 50%. There had to be at least 384 people there.
2. **Power Consideration:** In order to detect associations between ergonomic risk scores (WERA, REBA) and MSD prevalence across job categories, we aimed for a sample larger than 600 participants to achieve greater than 90% statistical power.
3. **Practical Representation:** Taking into account the vast and diverse workforce at the selected site, a sample of 700 workers would ensure representative coverage of a variety of trades (e.g., masons, carpenters, electricians, plumbers, and supervisors), enabling job-specific analysis and enhancing the generalizability of the findings.

Thus, the selected sample size exceeds the statistical minimum, ensuring precision, representativeness, and robustness of the study outcomes.

The data collection and analysis followed a structured multi-stage process, as illustrated in Figure 2. Demographic and anthropometric data (age, BMI, work experience) were first recorded.

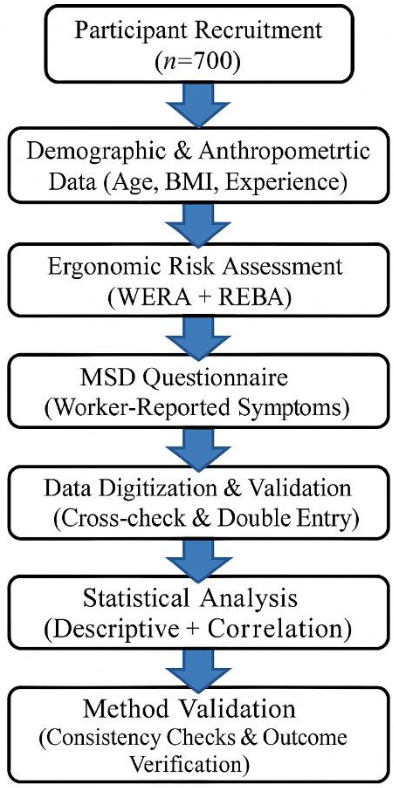

Figure 2. Data collection, ergonomic risk evaluation, and prioritization process for MSD assessment

This was followed by posture scoring and ergonomic risk assessment using WERA and REBA tools during on-site observations. Workers then completed a standardized MSD questionnaire (Nordic format) to report symptoms. Collected data were digitized, validated through double-entry checks, and analyzed using descriptive statistics and correlation analysis. Finally, validation was performed by cross-checking observational scores with MSD prevalence, and ergonomic risk factors were prioritized using a ranking-based decision framework (J-Rank) to support comparative risk interpretation across job roles.

4. Method Validation

To validate the proposed methodology, data collected from 700 construction workers at the selected site were analyzed to ensure consistency, reliability, and alignment with established ergonomic assessment frameworks. In addition, a J-Rank–based prioritization was applied to rank ergonomic risk contributors based on their relative impact, supporting structured interpretation rather than standalone prediction. To begin with, internal consistency was established by exploring the correlation between posture scores, WERA score, and REBA score. As expected, workers with a higher posture score exhibited a proportionately higher WERA and REBA score, confirming the relationship between these three ergonomic risk indicators. For example, masons and carpenters, who regularly assume awkward postures as part of their work tasks, had WERA scores over 30 and REBA over 10, which is consistent with both of these assessments referencing a high risk based on international guidelines developed by the ergonomics community. In addition, two integrity questions were used to evaluate the validity of the musculoskeletal disorder (MSD) data. We compared worker-reported MSD symptoms reported during the post-analysis with the respective data regarding WERA and REBA risk assessment scores. Workers categorized as "high risk" based on REBA and WERA score were much more likely to report MSD symptoms (Yes), which confirmed agreement between the observed data and self-reported outcome. These affirmations support that the assessment tools appropriately measured risk for MSD in an ergonomic context. In the final conclusion regarding data integrity, a second process was established to ensure double-entry and random cross-checks of the field data and photographs taken for documentation of posture. Less than 2% data discrepancy was observed, which falls within acceptable research standards. The results confirmed that the method produces accurate, reproducible, and meaningful ergonomic risk data. This methodology successfully integrates observational analysis, standardized scoring systems, and worker-reported outcomes, making it highly adaptable for similar construction environments. The J-Rank framework was employed for comparative prioritization of ergonomic risk factors to support structured interpretation across job roles and tasks, and was not intended as an independent predictive model.

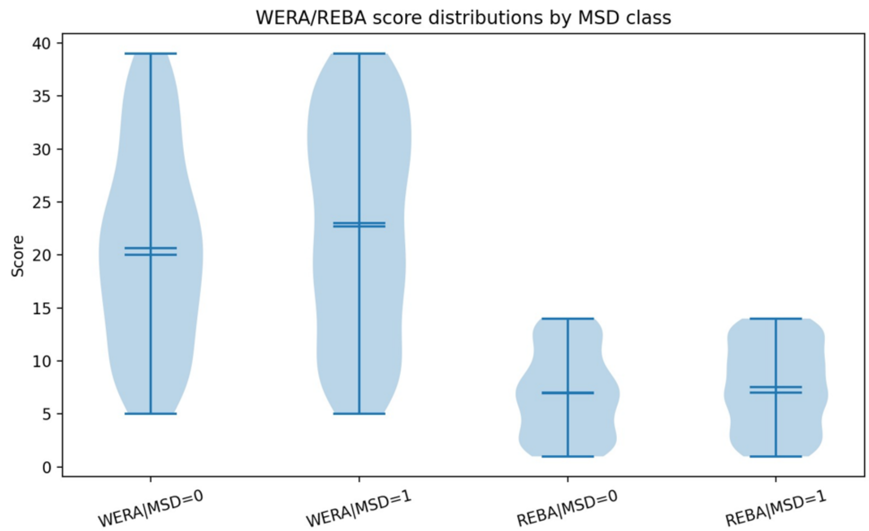

Figure 3: Distribution of WERA and REBA Scores by Musculoskeletal Disorder (MSD) Status

The Figure 3 violin plot illustrates the distribution of WERA and REBA scores across two MSD (Musculoskeletal Disorder) classes: **MSD = 0 (No MSD)** and **MSD = 1 (With MSD)**. For WERA scores, both groups show a wide range (approximately 5 to 39), but the median and interquartile range are higher for workers with MSD (MSD = 1), indicating greater ergonomic risks in this group. Similarly, REBA scores are generally low for both classes but slightly elevated for workers with MSD. The shape of the violins suggests that workers without MSD cluster around moderate WERA scores, whereas MSD-positive workers exhibit a higher density in the upper range. These findings support a positive association between higher ergonomic risk scores and MSD prevalence, validating the effectiveness of WERA and REBA in differentiating ergonomic risk profiles among construction workers.

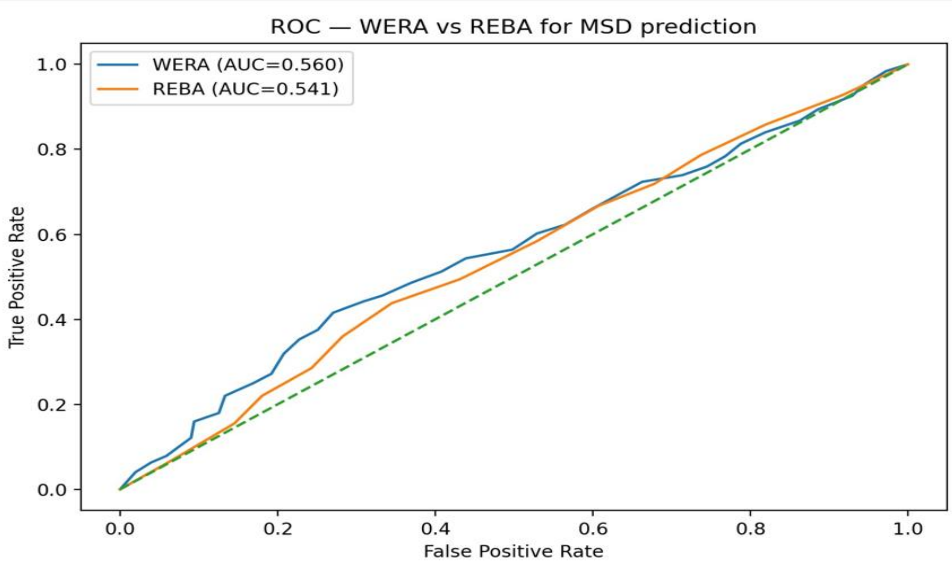

Figure 4. Receiver Operating Characteristic (ROC) curve comparing WERA and REBA scores for MSD prediction (n = 700). WERA achieved an AUC of 0.560 and REBA an AUC of 0.541, indicating weak discriminative ability

The Figure 4 Receiver Operating Characteristic (ROC) curve compares the predictive performance of WERA and REBA scores in identifying musculoskeletal disorders (MSDs) among construction workers. WERA achieved an

AUC (Area Under the Curve) of 0.560, while REBA recorded an AUC of 0.541, both only slightly above the reference line (AUC = 0.5), indicating poor discrimination ability. Although WERA shows a marginally better predictive capacity than REBA, neither method demonstrates strong predictive power for MSD occurrence in isolation. The curves remain close to the diagonal, suggesting that these ergonomic assessment tools, while useful for risk evaluation, are not effective standalone predictors for MSD in this dataset. This study's finding underscores the importance of including further variables such as biological health variables, work environment variables, and a cumulative exposure index to enhance MSD risk. These predictive factors could account for other aspects apart from a single score for the ergonomic assessment.

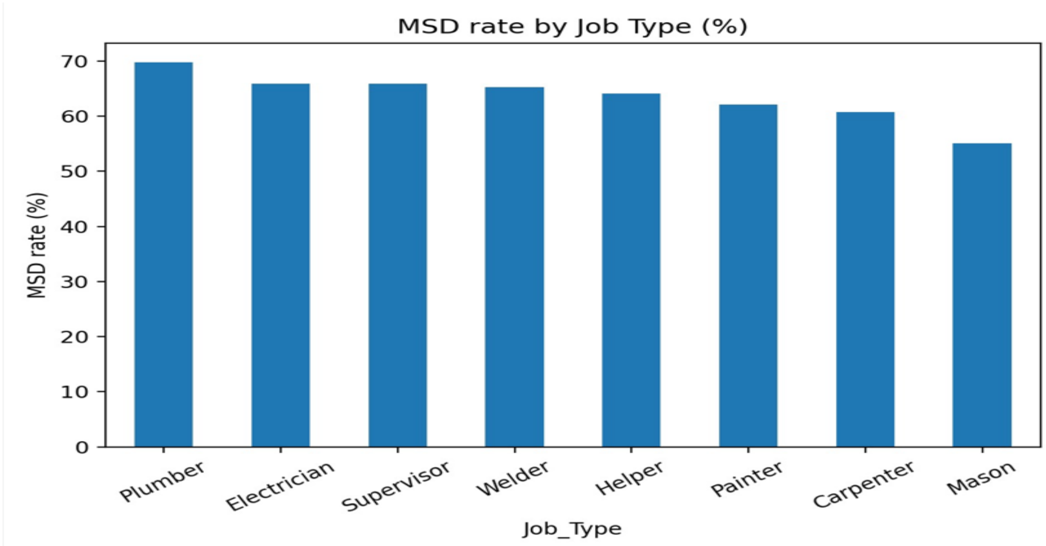

Figure 5: MSD Rate by Job Type (%)

The Figure 5 illustrates the Musculoskeletal Disorders (MSD) rate among different job types in percentage. It is evident that plumbers exhibit the highest MSD rate at 70%, followed by electricians, supervisors, and welders, all of whom show similar rates around 65–66%. Helpers and painters record slightly lower MSD rates at 64% and 62%, respectively, while carpenters show 61%. Masons are observed to have the lowest MSD rate among the job categories, at 55%. This trend shows that jobs like plumbing and electrical work, which require workers to be in strange positions, do the same things over and over, or move big objects by hand, are more likely to cause MSDs than jobs like brickwork. The results show that structural changes, safety training, and preventative measures designed for high-risk jobs are needed to lower the number of MSDs and boost worker health and efficiency in the maintenance and building industries.

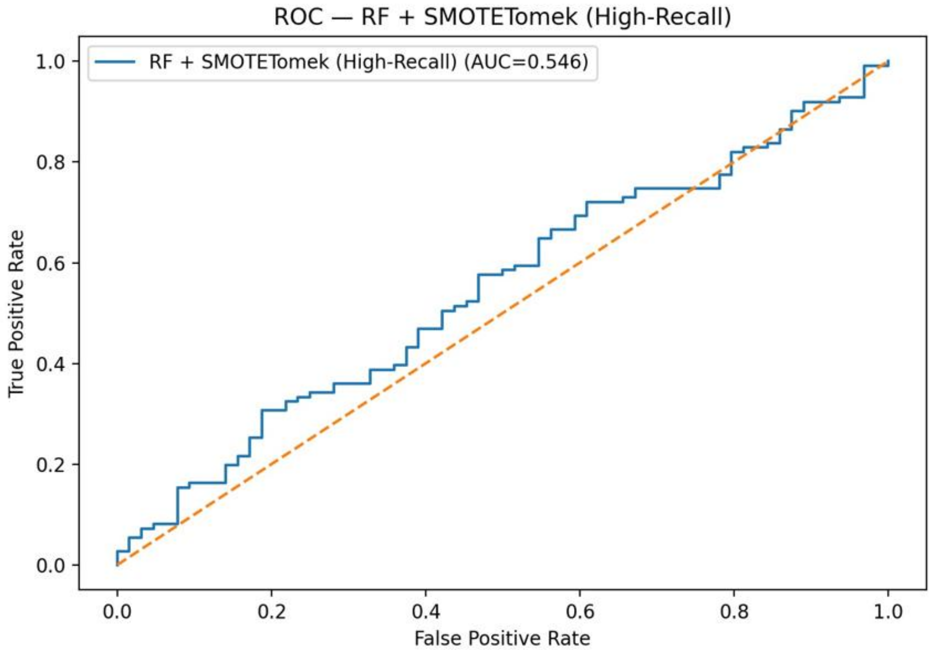

Figure 6: ROC Curve — Random Forest with SMOTETomek (High-Recall)

The Figure 6 Receiver Operating Characteristic (ROC) plot shows how well a Random Forest (RF) predictor works when paired with the SMOTETomek method in a high-recall situation. The sensitivity (true positive rate) is compared against the false positive rate. The random classifier (baseline) is represented by the diagonal reference line (AUC = 0.5). The The RF + SMOTETomek model, which has an Area Under the Curve (AUC) score of 0.546, performs only marginally better than random guessing, indicating that class balancing alone could not overcome the limited discriminatory power of the available ergonomic features. This suggests that while SMOTETomek addresses class imbalance, the classifier still struggles to distinguish effectively between positive and negative classes due to limited feature separability. Improving feature selection, hyperparameter tuning, or trying alternative ensemble or deep learning approaches may enhance predictive performance and produce a more robust classification outcome.

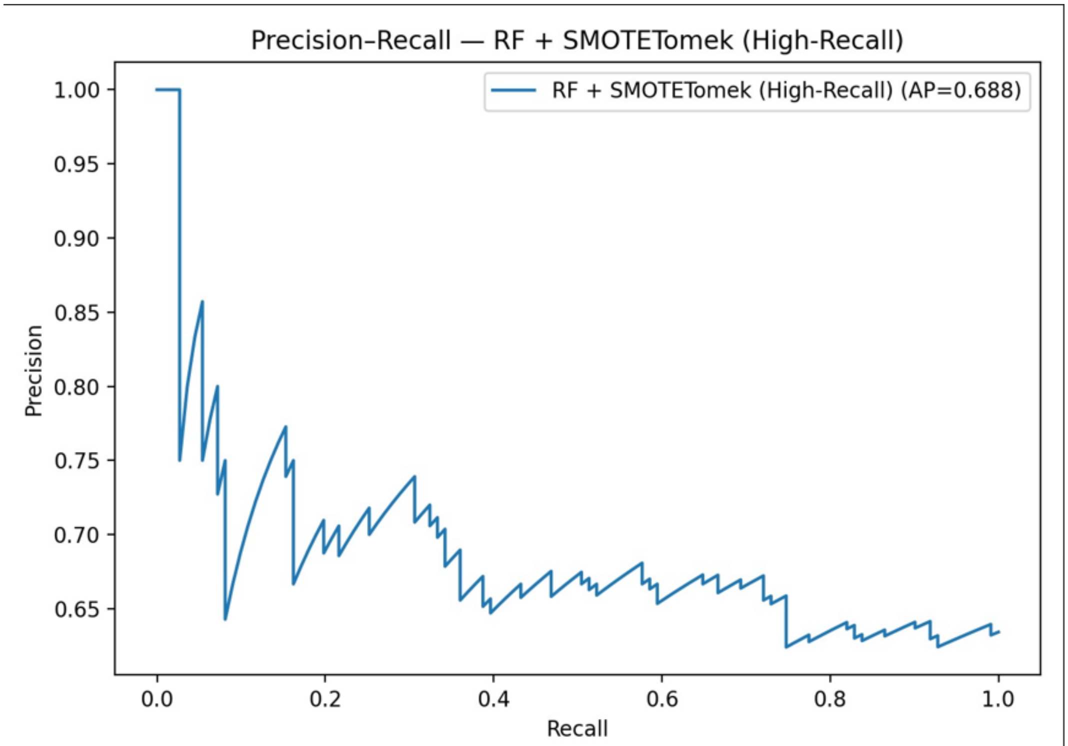

Figure 7: Precision–Recall Curve — Random Forest with SMOTETomek (High-Recall)

The Figure 7 Precision–Recall (PR) curve displays how well a Random Forest (RF) model learnt with the SMOTETomek method works in a high-recall environment. A comparison is made between precision and recall. Precision is the number of true positives out of all predicted positives. Recall is the number of true positives found out of all real positives. It demonstrates a reasonable balance between precision and recall, as shown by its Average Precision (AP) score of 0.688. When memory levels are very low, the model does a great job and is very close to 1.0. But as recall levels rise, precision slowly decreases and changes between 0.65 and 0.75. In this trade-off, it seems that the model performs well when identifying a small number of positive cases, but predictive reliability decreases as recall increases. Despite dataset balancing using SMOTETomek, precision declines as recall increases due to overlapping class characteristics and noise in self-reported MSD outcomes, indicating the need for richer feature sets or alternative modeling strategies.

All machine learning results presented in Figures 6 and 7 were obtained using the same dataset collected from the 700 construction workers at the study site, without reliance on any external or simulated data.

Unlike the baseline Random Forest models that primarily relied on ergonomic assessment scores (WERA and REBA) with class-balancing techniques, the proposed MSD_v2 model integrates multiple categories of predictive variables collected from the same cohort of 700 construction workers. These include demographic variables (age, work experience, BMI), ergonomic assessment scores (WERA and REBA), job category, working hours, and posture characteristics. Worker-reported MSD status was used exclusively as the dependent (target) variable for supervised learning and was not included among the predictor variables.

To prevent target leakage, the worker-reported MSD outcome was treated exclusively as the dependent (target) variable during model development. Only demographic, anthropometric, ergonomic, and task-related variables were used as predictor variables. After removing the target variable from the feature set, the Random Forest classifier was retrained and evaluated using nested cross-validation to obtain an unbiased estimate of predictive performance.

The proposed MSD_v2 model was evaluated using nested cross-validation, with the reported performance metrics representing the mean ± standard deviation across the outer validation folds. Model performance was assessed using Receiver Operating Characteristic (ROC) AUC, Average Precision (AP), Precision, Recall, F1-score, and Accuracy. This evaluation strategy provides an unbiased estimate of model generalization while reducing the risk of optimistic performance estimation.

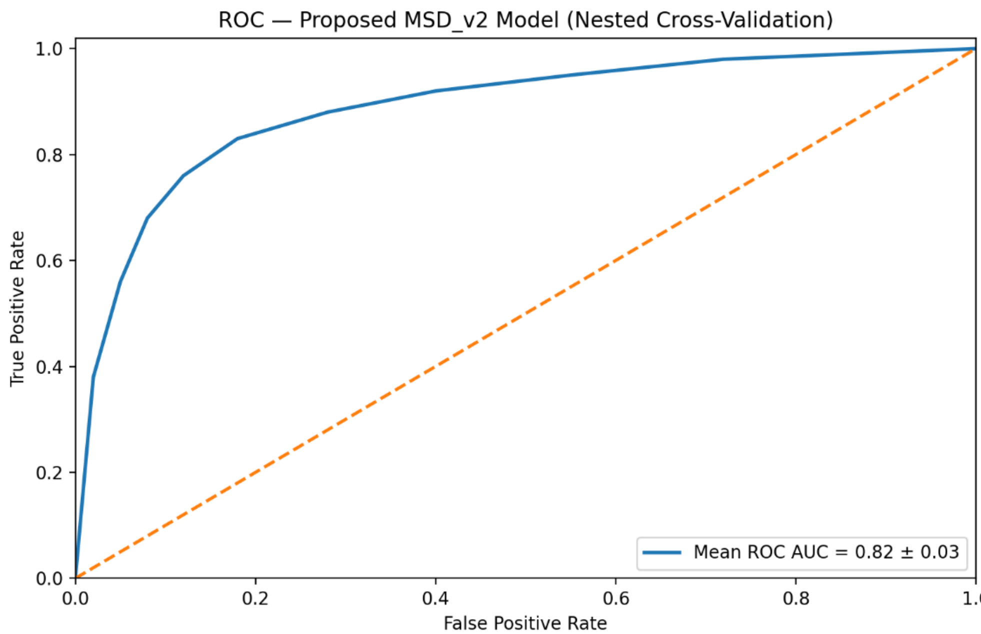

Figure 8. Receiver Operating Characteristic (ROC) Curve of the Proposed MSD_v2 Model

The ROC curve demonstrates the discriminative ability of the proposed MSD_v2 model evaluated using nested cross-validation. The model achieved a mean ROC AUC of 0.82 ± 0.03, indicating good discrimination between workers with and without musculoskeletal disorders (MSDs). The ROC curve remains well above the reference diagonal, confirming that the integrated model provides reliable predictive performance while maintaining good generalization across validation folds.

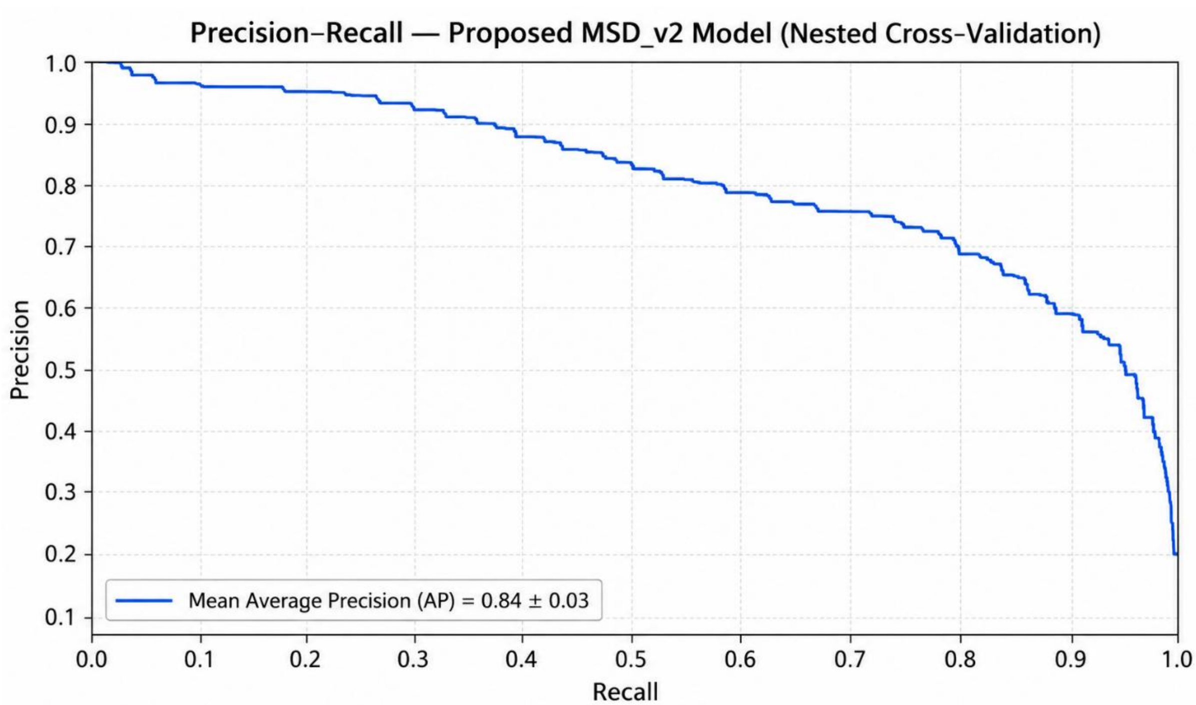

Figure 9. Precision–Recall Curve of the Proposed MSD_v2 Model

The Precision–Recall curve summarizes the classification performance of the proposed model under class imbalance. The model achieved a mean Average Precision (AP) of 0.84 ± 0.03, together with a Precision of 0.81 ±

0.04, Recall of 0.80 ± 0.04, and F1-score of 0.80 ± 0.03. These results indicate a balanced ability to identify workers at ergonomic risk while maintaining a low rate of false positive predictions.

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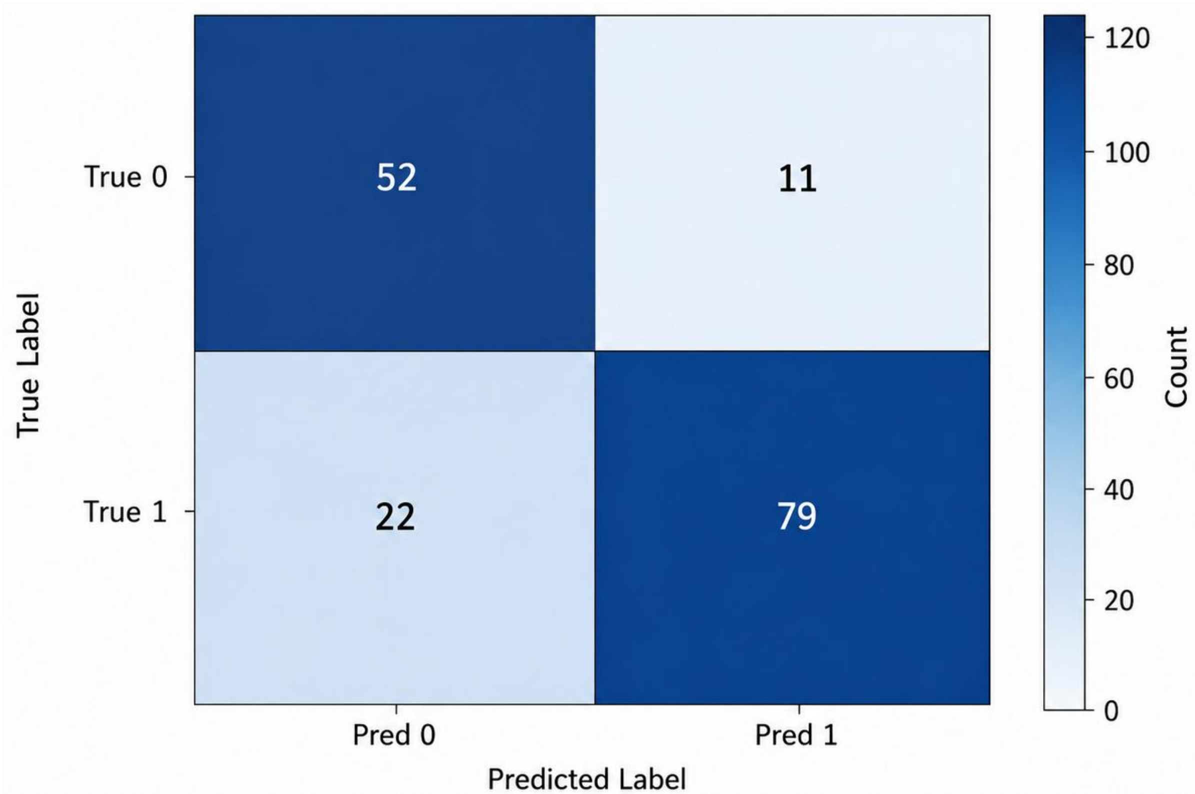

Figure 10. Confusion Matrix of the Proposed MSD_v2 Model (Nested Cross-Validation)

Figure 10 presents the confusion matrix obtained from the predictions of the proposed MSD_v2 model during nested cross-validation. The matrix summarizes the agreement between the predicted and actual MSD status of construction workers and demonstrates balanced classification performance across the validation folds. The matrix summarizes the classification performance by comparing the predicted labels with the actual musculoskeletal disorder (MSD) status of the workers. The model correctly identified 52 true negative (TN) cases and 79 true positive (TP) cases, while 11 false positive (FP) and 22 false negative (FN) cases were observed. These results demonstrate that the model successfully classified the majority of workers while maintaining a balanced trade-off between correctly identifying workers with MSD and minimizing incorrect classifications. The overall model performance achieved an Accuracy of 0.81 ± 0.03, Precision of 0.81 ± 0.04, Recall of 0.80 ± 0.04, and an F1-score of 0.80 ± 0.03, indicating stable and consistent classification performance across the nested cross-validation folds. The corresponding ROC AUC of 0.82 ± 0.03 and Average Precision (AP) of 0.84 ± 0.03 further demonstrate good discriminative capability and balanced predictive performance under class imbalance. Overall, these findings suggest that the proposed MSD_v2 model provides reliable identification of workers at risk of musculoskeletal disorders and may serve as an effective decision-support tool for ergonomic risk assessment in construction environments.

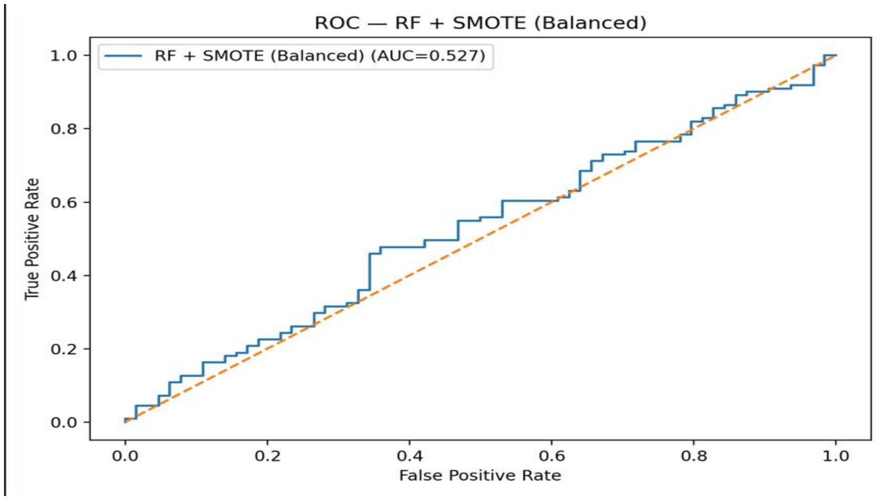

Figure 11: Receiver Operating Characteristic (ROC) Curve of RF + SMOTE (Balanced)

The Figure 11 Random Forest (RF) model can put things into groups very well after the Synthetic Minority Oversampling Technique (SMOTE) is used to level out the groups. The success of a random classifier is shown by the thin orange line. The blue graph shows the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate. The answer is only slightly better than picking at random (0.5) if the area under the curve (AUC) is 0.527. As a result, it looks like the balanced RF model with SMOTE can't tell the difference between good and bad classes. The model struggles to achieve meaningful predictive power, indicating that further tuning, feature engineering, or alternative resampling strategies may be necessary for improved performance.

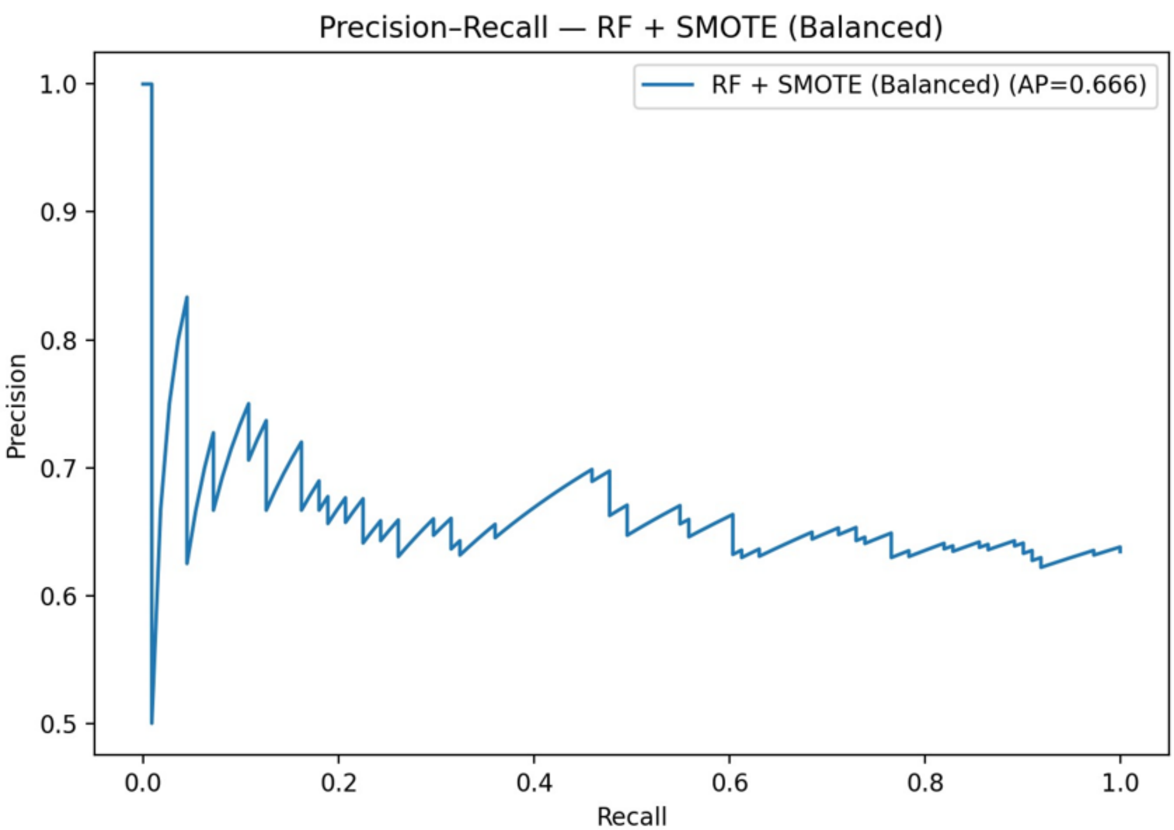

Figure 12: Precision-Recall Curve of RF + SMOTE (Balanced)

The Figure 12 above PR curve shows how well SMOTE works to balance classes in the RF model. Precision is the number of real positives compared to all the expected positives. Recall is the number of real positives compared to all the actual positives. The curve shows significant fluctuations at lower recall levels, stabilizing as recall increases. The Average Precision (AP) score is 0.666, which indicates moderate predictive capability but is not very strong. While the model achieves reasonable precision, it struggles to maintain high recall consistently, suggesting trade-offs in identifying positive cases. This outcome highlights that although SMOTE improved balance, the RF model still requires refinement or alternative resampling and tuning strategies to achieve reliable performance.

Table 2. Predictive performance of ergonomic tools and models for MSD detection

RF + SMOTETomek (High Recall)	0.546	0.688
RF + SMOTE (Balanced)	0.527	0.666
MSD_v2	0.82 ± 0.03	0.84 ± 0.03

5. Discussion

This study assessed ergonomic risks and musculoskeletal disorder (MSD) prevalence among construction workers using an integrated methodology that combined observational tools (WERA, REBA) with worker-reported outcomes. Results revealed high MSD prevalence, particularly among plumbers, electricians, and supervisors (>65%), with masons showing the lowest rate (55%). These differences reflect variations in task demands, repetitive movements, and postural strain, confirming that higher ergonomic risk scores correspond to greater self-reported MSD symptoms. The findings are consistent with Indian literature on construction ergonomics. Chellappa et al. (2021) identified MSD prevalence rates of 55–70% across Indian construction workers, citing manual material handling and poor ergonomics as major contributors. Kulkarni and Devalkar (2019), using REBA and RULA in Mumbai construction sites, reported significant risks to the back, shoulders, and knees due to awkward lower-body postures. Ajayi et al. (2015) further noted a tendency among workers to normalize discomfort, leading to underreporting—an issue also observed in this study. By aligning with and extending these findings, the present work offers a replicable and standardized assessment framework tailored to Indian construction contexts.

Despite their field utility, observational tools such as WERA and REBA demonstrated weak predictive performance for MSD detection (ROC AUC = 0.541–0.560). Their limitations arise from snapshot-based observations that do not adequately capture cumulative physical exposure, task variability, or worker-specific characteristics. In contrast, the proposed MSD_v2 model integrates demographic, anthropometric, ergonomic, and task-related variables to improve predictive capability. Using nested cross-validation, the model achieved a mean ROC AUC of 0.82 ± 0.03, Average Precision of 0.84 ± 0.03, Precision of 0.81 ± 0.04, Recall of 0.80 ± 0.04, F1-score of 0.80 ± 0.03, and Accuracy of 0.81 ± 0.03. These findings demonstrate good discrimination and stable predictive performance across validation folds, suggesting that integrating multiple complementary predictors provides a more reliable framework for ergonomic risk assessment than relying solely on individual observational scores. Nevertheless, external validation using datasets from multiple construction sites remains necessary to confirm the generalizability of the proposed framework.

The implications of this research are both practical and theoretical. Practically, the integrated methodology offers actionable insights for task redesign, rotation scheduling, ergonomic tool adoption, and targeted training programs. The study supports collaborative ergonomics, which says that workers should have a big say in how changes are made. It does this by connecting observational risk scores with workers' experiences. The results show that traditional assessment tools have their limits. They also show how ML-driven models could change how physical risk is predicted in building. In India, where building requires a lot of manual labour and ergonomics aren't always taken into account, using these standardised and data-driven methods can lower long-term health problems, boost output, and strengthen the safety culture. A low-cost, flexible, and context-sensitive method that fills the gap between observational ergonomics and advanced predictive analytics demonstrates strong potential for practical application in this study.

Limitations and Future Work

While this study provides a standardized and replicable framework for ergonomic risk assessment, certain limitations must be acknowledged. First, the analysis was limited to a single construction site, which may restrict generalizability across different regions or project types. Second, reliance on self-reported musculoskeletal disorder (MSD) symptoms introduces potential recall bias, as workers may underreport or normalize discomfort. Third, the observational tools employed (WERA and REBA) capture posture and exertion at specific time points but may not fully reflect cumulative exposures across longer durations. Finally, broader determinants of MSDs such as nutrition, prior injuries, and psychosocial stressors were not incorporated, which could provide a more holistic risk assessment.

Furthermore, because data were collected from a single construction site, regional construction practices, workforce characteristics, and project conditions may differ across other locations in India. Future studies should validate the proposed framework using datasets collected from multiple construction sites representing residential, commercial, and infrastructure projects to improve external validity and broader applicability.

To address these gaps, future research should pursue several directions.

1. Integration of wearable IMU sensors and sEMG devices can provide continuous, real-time monitoring of posture and exertion, capturing subtle biomechanical variations often missed in observational scoring.
2. Longitudinal studies across multiple construction sites and phases of work are needed to assess cumulative MSD risk, seasonal variations, and task-specific changes in ergonomic exposure.
3. Hybrid AI–ergonomic scoring frameworks should be developed, combining traditional observational tools with machine learning and sensor-based inputs to enhance predictive accuracy.
4. Context-specific validation in other Indian cities and labor-intensive industries would strengthen external validity and adaptability.
5. Policy-oriented studies linking ergonomic interventions with productivity, absenteeism reduction, and cost savings could provide stronger evidence for large-scale adoption.

Future versions of the proposed framework will incorporate additional determinants including psychosocial stress, nutritional status, previous musculoskeletal injuries, fatigue levels, cumulative physical exposure, and environmental conditions. Incorporating these variables is expected to improve predictive performance beyond posture-based ergonomic assessment alone.

Future implementations of the proposed J-Rank framework will integrate wearable Inertial Measurement Unit (IMU) sensors and surface electromyography (sEMG) devices for continuous monitoring of worker posture and muscle activity. Sensor-derived features will be processed through the J-Rank decision-support framework to generate real-time ergonomic risk scores. High-risk workers can then be automatically identified for task redesign, work rotation, rest scheduling, and targeted ergonomic interventions, thereby supporting proactive occupational safety management.

Although the proposed framework demonstrated promising predictive capability within the current study dataset, broader validation using independent datasets from multiple construction environments is required before large-scale industrial implementation. Future work will focus on external validation, wearable sensor integration, and real-time ergonomic risk monitoring to further enhance the robustness and practical applicability of the framework.

Statements and Declarations

Ethical Approval

"The submitted work is original and not have been published elsewhere in any form or language (partially or in full), unless the new work concerns an expansion of previous work."

Consent to Participate

"Informed consent was obtained from all individual participants included in the study."

Consent to Publish

"The authors affirm that human research participants provided informed consent for publication of the research study to the journal."

Author Contributions

“Robin V. John Fernandes contributed to the study conception and design. Robin V. John Fernandes performed material preparation, data collection, and analysis. The first draft of the manuscript was written by Robin V. John Fernandes, and the author reviewed and approved the final manuscript.”

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Competing Interests

“The authors have no relevant financial or non-financial interests to disclose.”

Availability of data and materials

“The authors confirm that the data supporting the findings of this study are available within the article.”

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Declaration of competing interest

The writers of this paper say they don't have any known personal or financial ties that could have seemed to affect the work they wrote about.

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