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### AI-based automated RULA and REBA assessment using video analysis for ergonomics risk evaluation

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#### Abstract

Advances in artificial intelligence (AI) and computer vision have enabled automated ergonomic risk assessment using video-based posture analysis. Traditional ergonomic evaluation methods such as RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment) are time-consuming, observer-dependent, and difficult to scale across large industrial operations. This study evaluates the feasibility and utility of a computer vision-based automated RULA and REBA assessment approach and discusses its opportunities and limitations in real-world workplace ergonomics. The investigation was conducted across industrial and office workstations in a manufacturing facility in Bangalore, covering a diverse range of tasks including receiving, incoming inspection, testing, debug and repair, packing, warehousing, and office work. Video recordings of 60 workers were analysed using TuMeke, an automated posture estimation system, to generate RULA and REBA scores. Additionally, head and neck posture was evaluated using the AI Posture Evaluation and Correction System (APECS), measuring cervical horizontal angle (CHA), craniovertebral angle (CVA), and shoulder sagittal plane angle (SSP). Results indicate that automated assessment efficiently identifies non-neutral postures and supports rapid ergonomic screening, with most tasks classified within low to moderate risk categories. However, findings also underscore the necessity of expert interpretation to account for task variability, cumulative load, and work context. The study concludes that AI-based ergonomic assessment is best employed as a decision-support tool, integrated with human factors expertise, to ensure accurate, context-sensitive, and responsible ergonomic risk evaluation.

**Keywords:** RULA, REBA, ergonomic risk assessment, computer vision, posture analysis, TuMeke, APECS, workplace ergonomics, AI-driven assessment, manufacturing

#### 1. Introduction

Musculoskeletal disorders (MSDs) represent one of the most prevalent and costly occupational health problems worldwide. According to the World Health Organization, MSDs are the leading contributor to global disability, with work-related MSDs substantially impacting productivity, worker well-being, and healthcare expenditure. In manufacturing and service industries, prolonged adoption of non-neutral postures, repetitive motions, and awkward working positions significantly elevate the risk of developing upper limb, neck, and back disorders.

Ergonomic risk assessment tools such as the Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) are widely validated methods for quantifying postural risk in occupational settings. RULA focuses on the upper extremities, wrists, forearms, upper arms, and neck and assigns a risk score to guide intervention priorities. REBA extends this to include whole-body postures, incorporating trunk, legs, and load/force requirements, making it particularly suitable for dynamic, unpredictable activities.

Despite their effectiveness, traditional RULA and REBA assessments are manual, observer-dependent, and resource-intensive. An ergonomist must directly observe workers,

record posture data, and score each body segment, a process that is impractical for large-scale or continuous monitoring. Inter-rater variability is also a recognized limitation, where two trained observers may assign differing scores for the same task.

The emergence of AI-driven computer vision technologies offers a promising solution to these challenges. Pose estimation algorithms, such as those used in platforms like TuMeke, can automatically detect skeletal joint positions from standard video footage and compute ergonomic scores in near real-time. This enables scalable, objective, and cost-efficient ergonomic screening across multiple workstations and shifts.

This paper evaluates the practical application of computer vision-based RULA and REBA assessment in a real-world manufacturing environment. It presents findings from a study conducted at a manufacturing facility in Bangalore, India, assesses the risk levels identified across diverse workplace tasks, and critically examines the strengths and limitations of AI-based ergonomic tools as part of an integrated occupational health strategy.

#### 2. Objectives

The specific objectives of this study were:

- To evaluate the feasibility of computer vision-based automated RULA and REBA assessment in industrial and office workstations.
- To identify ergonomic risk levels across different workplace tasks using automated posture analysis.
- To examine the opportunities and limitations of AI-driven ergonomic assessment as a decision-support tool in occupational health practice.

### 3. Review of Literature

#### 3.1 Traditional Ergonomic Assessment Methods

RULA was developed by McAtamney and Corlett (1993) [5] as an observational method to assess the exposure of individual workers to ergonomic risk factors associated with upper limb work-related disorders. It evaluates postures of the upper arm, lower arm, wrist, neck, trunk, and legs, producing a grand score from 1–7 that indicates urgency for intervention. REBA, introduced by Hignett and McAtamney (2000) [3], extended this approach to the whole body and incorporated dynamic load handling, becoming the preferred tool for assessing jobs involving unpredictable postures such as those in healthcare and logistics.

Both tools have been extensively validated and are recommended by occupational safety standards globally. However, they are inherently observational, relying on trained ergonomists to capture task postures at representative moments, which introduces subjectivity and limits their scalability. Studies have noted inter-rater reliability challenges, with intraclass correlation coefficients varying widely across assessors (Dempsey & Mathiassen, 2006) [2].

#### 3.2 AI and Computer Vision in Ergonomics

The integration of machine learning and computer vision into ergonomic assessment has been an active research area since the mid-2010s. Deep learning-based pose estimation models, such as OpenPose (Cao *et al.*, 2017) [1], AlphaPose, and MediaPipe, can detect 2D or 3D skeletal joint coordinates from video footage with high accuracy, enabling automated computation of joint angles and postural classifications.

Several studies have demonstrated the validity of automated RULA and REBA scoring against manual expert assessment. Vignais *et al.* (2013) [6] showed that inertial measurement unit (IMU)-based systems could produce RULA scores comparable to observational methods. More recently, RGB camera-based systems have achieved similar or superior reliability. Platforms such as TuMeke leverage these technologies to provide real-time ergonomic risk feedback from standard video recordings, making them practically deployable in industrial settings.

Despite the promise of automation, a number of limitations persist. Occlusion of body segments, variation in camera angle, clothing effects on joint detection, and the inability to assess contact forces or tool use represent ongoing challenges. Moreover, automated systems may not capture the full temporal context of a task, cumulative exposure over a shift, which is an important determinant of MSD risk (Mathiassen, 2006) [4].

### 4. Materials and Methods

#### 4.1 Study Design and Setting

This study employed a cross-sectional observational design.

The investigation was conducted at two operational units of a manufacturing facility located in Bangalore, Karnataka, India. The facility produces electronics components and operates under standard shift conditions. Work areas assessed included receiving, incoming inspection, testing, debug and repair, shipment packing, warehousing (stores), final inspection and quality assurance, and office workstations, providing a comprehensive representation of both industrial and sedentary occupational tasks.

#### 4.2 Participants

A total of 60 workers participated in the study ( $n = 60$ ). Workers were purposively selected to represent all major task categories across both study units. Participation was voluntary, and all participants provided informed consent prior to data collection. Ethical clearance was obtained from the institutional review board prior to the commencement of the study.

#### 4.3 Instrumentation

Two primary tools were employed for automated postural assessment:

**TuMeke (Computer Vision-Based Posture Estimation System):** TuMeke uses AI-powered skeletal detection to analyse video recordings of workers performing their tasks. The system automatically identifies joint positions frame-by-frame, computes joint angles, and generates RULA and REBA scores in accordance with established scoring methodologies. It provides risk classification outputs on a per-task basis, enabling rapid ergonomic screening without the need for manual observation.

**APECS (AI Posture Evaluation and Correction System):** APECS was used specifically for head and neck postural assessment. It measures three key angular parameters:

- **Cervical Horizontal Angle (CHA):** The angle of the cervical spine relative to the horizontal plane. Higher CHA values indicate greater forward head flexion and increased cervical spine loading.
- **Craniovertebral Angle (CVA):** The angle formed between the tragus of the ear and the seventh cervical vertebra. Lower CVA values indicate more pronounced forward head posture and increased strain on the neck and shoulder musculature.
- **Shoulder Sagittal Plane Angle (SSP):** The angle of shoulder position in the sagittal plane. Higher SSP values indicate shoulder protraction, associated with elevated upper back muscle loading.

#### 4.4 Data Collection Procedure

Video recordings of workers performing their designated tasks were captured using standard digital cameras. Cameras were positioned to provide clear views of full-body posture, with additional close-up angles for head and neck analysis. Recordings covered representative task cycles for each work area. Videos were subsequently uploaded to the TuMeke platform for automated RULA and REBA scoring, and to the APECS system for head and neck postural analysis.

RULA assessments were completed for 20 representative observations across the task categories ( $n = 20$  per RULA analysis), while REBA assessments covered a broader

sample of 40 observations ( $n = 40$  per REBA analysis) to account for the greater variety of whole-body postures encountered in manufacturing tasks.

#### 4.5 Risk Classification Criteria

RULA scores are interpreted on a scale of 1–7, where scores of 1–2 indicate acceptable posture, 3–4 suggest further investigation is warranted, 5–6 indicate the need for prompt investigation and change, and 7 indicates immediate intervention is required. REBA scores are similarly categorised: 1 is negligible risk, 2–3 is low risk, 4–7 is medium risk, 8–10 is high risk, and 11+ is very high risk.

### 5. Results

#### 5.1 RULA Scores ( $n = 20$ )

RULA scores across the assessed tasks ranged from 3 to 5, placing the majority of activities in the 'further investigation required' to 'investigate and change soon' categories. The distribution of RULA scores across the 20 observations is summarised in Table 1. Scores of 3 and 4 were most frequently observed across receiving, inspection, and office tasks. Scores of 5 were recorded for tasks involving sustained forward reaches and overhead work in debug and repair and packing stations.

**Table 1:** Summary of RULA Scores by Work Area ( $n = 20$ )

| Task / Work Area      | RULA Score Range | Risk Category                   |
|-----------------------|------------------|---------------------------------|
| Receiving             | 3–4              | Investigate Further             |
| Incoming Inspection   | 3–4              | Investigate Further             |
| Testing               | 3–4              | Investigate Further             |
| Debug & Repair        | 4–5              | Investigate / Change Soon       |
| Shipment / Packing    | 4–5              | Investigate / Change Soon       |
| Final Inspection & QA | 3–4              | Investigate Further             |
| Stores / Warehousing  | 3–5              | Investigate Further–Change Soon |
| Office Work           | 3–4              | Investigate Further             |

#### 5.2 REBA Scores ( $n = 40$ )

REBA scores ranged from 2 to 8 across the assessed tasks, indicating a spectrum from low to high ergonomic risk. The majority of tasks (approximately 70%) were classified within the low to medium risk range (REBA scores 2–7). Tasks involving manual material handling, extended periods of standing with forward trunk flexion (receiving, stores), and tasks requiring precise hand work at non-ideal heights (testing, debug and repair) produced higher REBA scores. A subset of observations in warehousing and packing yielded REBA scores of 8, denoting high risk and necessitating investigation and change. Results are summarised in Table 2.

**Table 2:** Summary of REBA Scores by Work Area ( $n = 40$ )

| Task / Work Area      | REBA Score Range | Risk Level  |
|-----------------------|------------------|-------------|
| Receiving             | 5–8              | Medium–High |
| Incoming Inspection   | 3–5              | Low–Medium  |
| Testing               | 3–5              | Low–Medium  |
| Debug & Repair        | 4–6              | Medium      |
| Shipment / Packing    | 5–8              | Medium–High |
| Final Inspection & QA | 3–5              | Low–Medium  |
| Stores / Warehousing  | 5–8              | Medium–High |
| Office Work           | 2–4              | Low–Medium  |

#### 5.3 Head and Neck Posture Analysis (APECS)

APECS analysis of head and neck posture revealed notable deviations from neutral alignment across several workstations. Elevated CHA values were recorded in testing and office workstations, suggesting significant forward head flexion and heightened cervical spine loading. Reduced CVA values were observed in workers performing close-proximity inspection tasks, indicating forward head posture with associated neck and shoulder strain. Elevated SSP angles were noted in workers performing tasks involving extended reaching or working below elbow height, consistent with shoulder protraction and upper back muscle loading. These findings complement the RULA and REBA scores by providing additional granularity on head-neck postural risk, which is particularly relevant for sedentary office workers and precision assembly operators.

### 6. Discussion

#### 6.1 Opportunities of AI-Based Ergonomic Assessment

The results of this study demonstrate that computer vision-based RULA and REBA assessment can effectively identify non-neutral postures and ergonomic risk levels across a diverse range of industrial and office tasks. The automated system enabled consistent and rapid screening of 60 workers across multiple work areas a scale that would have required substantially more time and personnel using traditional observational methods.

A key advantage of AI-driven assessment is its objectivity. Unlike manual RULA and REBA evaluations, which are susceptible to observer bias and inter-rater variability, automated pose estimation applies consistent algorithmic criteria to all observations. This is particularly valuable in large organisations seeking to standardise ergonomic monitoring programmes or conduct longitudinal comparisons of risk levels over time.

The integration of APECS for head and neck posture analysis adds a valuable dimension not typically captured by standard RULA and REBA assessments. By quantifying CHA, CVA, and SSP parameters, APECS provides nuanced data on postural deviations in the cervical and shoulder region, an area of growing concern given the rise of screen-based and precision assembly work.

Furthermore, video-based assessment is non-intrusive and can be conducted without disrupting normal work operations. Workers do not need to wear sensors or markers, and recordings can be analysed retrospectively, offering flexibility in data collection scheduling.

#### 6.2 Limitations of Automated Assessment

Despite these advantages, several important limitations were identified. First, automated systems may struggle with tasks involving occlusion, where body segments are obscured by equipment, other workers, or the worker's own clothing. In such cases, pose estimation accuracy decreases, potentially producing erroneous or incomplete scores.

Second, automated RULA and REBA scores represent instantaneous postural snapshots or averages over recorded intervals, but do not fully capture the cumulative exposure experienced by a worker over the course of a full shift. Cumulative biomechanical load, a key determinant of MSD risk, requires more sophisticated exposure assessment models that account for the frequency, duration, and

magnitude of postural deviations across the working day.

Third, task context and work organisation factors, such as production pace, task variety, recovery opportunities, and psychosocial stressors are not captured by posture estimation algorithms. These factors are integral to comprehensive ergonomic risk assessment and can substantially modify the risk implied by a given postural score.

Fourth, while the systems used in this study provide risk scores, the interpretation of these scores and the formulation of effective ergonomic interventions requires domain expertise. Automated tools identify where the risk exists, but they cannot independently determine why the risk exists or what the most appropriate intervention strategy would be. Over-reliance on automated outputs without expert interpretation may lead to inadequate or misdirected interventions.

### 6.3 AI as a Decision-Support Tool

Given these opportunities and limitations, this study affirms that AI-based ergonomic assessment is most effectively positioned as a decision-support tool rather than a standalone assessment method. In this role, automated RULA and REBA screening can serve as the first tier of a multi-stage ergonomic evaluation process, efficiently identifying high-risk tasks and workstations for priority attention, thereby enabling ergonomists to direct their expertise where it is most needed.

Integration with expert human factors evaluation is essential to contextualise automated findings, account for cumulative exposure and work organisational factors, and develop targeted interventions. This hybrid model leverages the scalability and consistency of AI while preserving the interpretive depth of human expertise.

## 7. Conclusions

This study evaluated the feasibility and utility of computer vision-based automated RULA and REBA assessment in a real-world manufacturing environment. The principal conclusions are as follows:

- AI-driven posture analysis using TuMeke effectively identified non-neutral postures across a diverse range of industrial and office tasks in a manufacturing facility.
- Most tasks were classified within the low to moderate ergonomic risk range, with higher risks observed in tasks involving manual material handling, sustained forward trunk flexion, and precision assembly work.
- Automated assessment enabled rapid, consistent, and scalable ergonomic screening of multiple workstations and workers, a significant operational advantage over traditional observational methods.
- APECS-based head and neck posture analysis provided additional granularity on cervical and shoulder risk, complementing standard RULA and REBA assessments.
- Sole reliance on automation is limited by task variability, work context factors, challenges, and the inability to quantify cumulative load exposure.
- AI-based ergonomic assessment is best used as a decision-support tool, integrated with expert human factors analysis, to ensure accurate, context-sensitive, and responsible risk evaluation and intervention

planning.

These findings support the adoption of AI-based ergonomic tools as part of proactive occupational health management programmes, provided they are deployed within a robust framework that includes expert oversight, periodic validation, and integration with broader workplace health initiatives.

## 8. Recommendations

Based on the findings of this study, the following recommendations are proposed for organisations implementing ergonomic assessment programmes:

- Use computer vision-based RULA and REBA tools for initial ergonomic risk screening across all workstations, with priority given to tasks identified as medium to high risk.
- Integrate automated assessment results with expert human factors evaluation to contextualise risk scores, account for cumulative exposure, and develop targeted ergonomic interventions.
- Prioritise workstation redesign for moderate and high-risk tasks, with particular attention to work surface height, reach distances, and material placement to promote neutral postures.
- Introduce structured job rotation schedules and scheduled micro-breaks to reduce cumulative biomechanical load on high-demand body regions.
- Improve ergonomic conditions at receiving, packing, and warehousing workstations, where higher REBA scores indicate significant whole-body postural risk, through workstation height adjustment and provision of mechanical aids.
- Provide targeted ergonomic training to workers and supervisors to reinforce posture awareness, correct technique, and the rationale for ergonomic controls.
- Incorporate AI-based ergonomic tools into periodic ergonomic audit cycles rather than as one-time assessments, enabling trend monitoring and evaluation of intervention effectiveness.
- Invest in further validation of AI-based RULA and REBA tools against expert observational benchmarks in varied occupational settings to strengthen the evidence base for their clinical and occupational health application.

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