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Bhagyashree P
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Sunil Shirwal
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Raviraj J
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Anusha S
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Santosh W
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Corresponding Author:
Bhagyashree P
Department of Farm Machinery
and Power Engineering, College of
Agricultural Engineering,
University of Agricultural Sciences,
Raichur, Karnataka, India

Ergonomic risk assessment methods in agriculture: A comprehensive review of tools and techniques

Bhagyashree P, Sunil Shirwal, Raviraj J, Anusha S and Santosh W

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Abstract

Work-related musculoskeletal disorders (WMSDs) remain one of the leading causes of occupational disability worldwide, with agricultural workers experiencing a disproportionately high risk due to repetitive tasks, awkward postures, forceful exertions, and adverse environmental conditions. The unique physical demands of agricultural operations - ranging from above-shoulder harvesting to prolonged under-knee tasks necessitate specialized ergonomic risk assessment approaches beyond conventional industrial tools. This review critically examines existing ergonomic risk assessment methods with particular emphasis on their applicability to agricultural work systems. The study systematically classifies assessment techniques into qualitative (questionnaires and self-reports), semi-quantitative (observational posture-based tools), quantitative (physiological and biomechanical measurements), and advanced digital methods incorporating computer vision and artificial intelligence. Widely used tools such as the rapid upper limb assessment (RULA), rapid entire body assessment (REBA), ovako working posture analysing system (OWAS), Agricultural upper-limb assessment (AULA), postural ergonomic risk assessment (PERA) and novel ergonomic postural assessment (NERPA) are comparatively analyzed in terms of scoring structure, reliability, agreement with specialist evaluations, correlation with WMSD prevalence and predictive validity. The findings indicate that while RULA demonstrates high predictive validity for upper-limb disorders, REBA provides broader whole-body coverage and AULA shows superior agreement in agriculture-specific contexts. However, most traditional tools rely heavily on static posture analysis and neglect dynamic biomechanical variables such as velocity and acceleration. The review further highlights the transition toward sensor-based and computer-vision-driven ergonomic assessment systems under the Industry 4.0 paradigm. Emerging approaches integrating motion capture, surface electromyography, inertial measurement units and machine learning algorithms offer improved objectivity and real-time monitoring but remain limited by cost, intrusiveness and environmental sensitivity. Overall, the analysis reveals that no single method provides a comprehensive solution for ergonomic risk evaluation in agriculture. A hybrid framework integrating observational tools with biomechanical and AI-based systems is recommended for accurate, dynamic and sector-specific ergonomic assessment. Future research should focus on incorporating kinetic and kinematic variables, improving angular sensitivity and developing integrated models tailored to agricultural operations.

Keywords: Ergonomics, Agriculture, WMSDs, REBA, RULA, OWAS, PERA, Risk Assessment.

Introduction

Work-related musculoskeletal disorders (WMSDs) are a critical global health issue, causing significant pain in muscles, tendons, ligaments, and nerves due to repetitive tasks and mechanical overload. These disorders are a primary driver of work-related disability and economic loss, accounting for more than 50% of all work-related diseases in the European Union and causing an estimated \$27 billion in annual costs to American industry (Bao *et al.*, 2009; Griffin 2012; Grandjean & Kroemer 1997) [2, 15, 16, 26]. Agricultural and industrial health initiatives now focus on early ergonomic interventions to mitigate these risks and rectify workplace deficiencies.

Importance of Ergonomics in Agriculture (Physical Demands)

Ergonomics is vital in the agricultural sector, which currently faces a demographic crisis: the growth of the elderly population in rural areas is outpacing overall growth, while a decrease in

farming households has caused a severe reduction in the available labor force. Consequently, the remaining workers experience much higher labor intensity. Agricultural work is uniquely demanding, involving frequently occurring awkward postures and repetitive activities that are often more strenuous than those in typical industrial sectors. As a result, the prevalence of WMSDs among farm-workers (61.5%) is approximately 2.5 times higher than in other occupational fields, with the most common injuries affecting the trunk, shoulders, and hand/wrist (Karwowski 2006; Gao *et al.*, 2025) [14, 23].

Ergonomical need for major agricultural operations

The mechanical load on agricultural workers is primarily dictated by the nature of the handled crop and its working height. Specific ergonomic needs are identified for the following operations:

- Above-shoulder Tasks: Operations involving crops such as grapes, peaches, tangerines, and pears require prolonged overhead reaching, leading to significant upper-limb stress (Donisi *et al.*, 2022; Madeleine 2010) [11, 28].
- Waist-level tasks: Operations for crops like rice and chrysanthemums involve repetitive bending and twisting at the waist.
- Under-knee tasks: Harvesting or maintaining strawberries, cucumbers, tomatoes, and oriental melons necessitates extreme trunk flexion and working in crouched or kneeling

positions. Because traditional industrial tools often underestimate the risk of these unique agricultural postures, specialized tools like the (AULA) have been developed to evaluate the specific postures required by these tasks (David 2005; Hedge *et al.*, 1999) [10, 19].

Need for ergonomic assessment

The ergonomic assessment process follows an interconnected cycle for identifying workplace risks and improving worker safety and performance. It begins with jobsite data acquisition and activity recognition, followed by motion capture simulation, 3D virtual model creation, data analysis, ergonomics risk analysis, and ergonomic risk rating (Jones, T., & Kumar 2007; Dul 2003) [12, 21]. This integrated approach helps identify ergonomic deficiencies, design safer work systems, and implement effective control measures to reduce workplace injuries and musculoskeletal disorders. The workflow connects motion capture, virtual modeling, data analysis, and risk evaluation in a systematic ergonomic assessment process, as shown in Figure 1. The integration of these stages improves the accuracy of ergonomic evaluation and supports better decision-making for workplace interventions. It also enables continuous monitoring and assessment of worker posture, movement, and biomechanical stress during task performance.

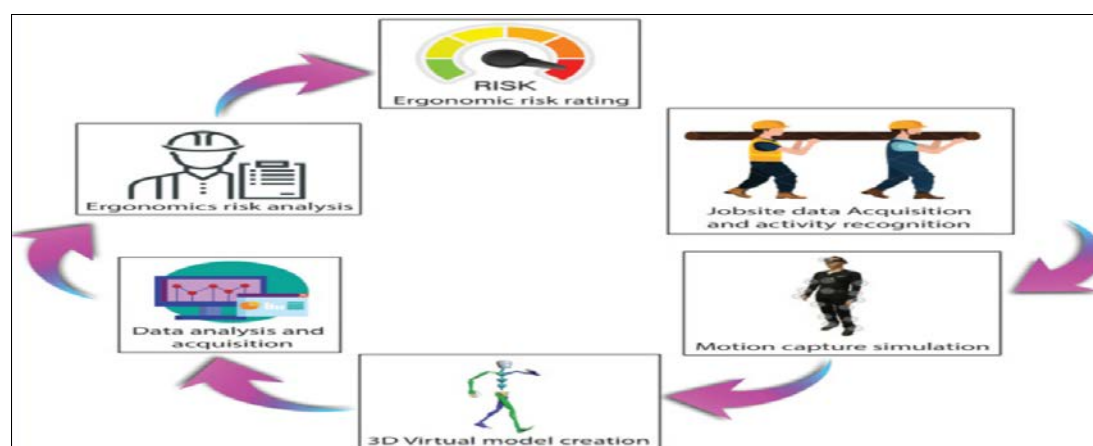


Fig 1: Workflow for the ergonomics risk assessment using motion capture technology.

Evolution of Ergonomic Assessment Methods (Traditional → Digital)

The methodology for assessing ergonomic risk has undergone a significant technological shift. Ergonomic assessment methods have evolved from subjective self-assessment questionnaires (e.g., Standard Nordic Questionnaire) to observational techniques such as RULA, REBA, and OWAS, which use posture-based checklists but are limited by observer bias (Karhu *et al.*, 1997; McAtamney & Corlett, 1993; Hignett & McAtamney, 2000) [20, 22, 30]. Advances in technology introduced direct measurement methods, including electrogoniometers and electromyography (EMG), for objective biomechanical data collection. More recently, computer vision and machine learning have enabled automatic, markerless posture assessment from video using models such as OpenPose. The latest developments integrate kinematic and kinetic parameters (e.g., velocity, acceleration, and force) to provide a more accurate and comprehensive evaluation of physical workload and musculoskeletal risk (Cao *et al.*, 2021; Gallagher and Heberger 2013) [4, 13].

2. Overview of ergonomic risk factors in agriculture Physical Risk Factors

The major ergonomic risk factors contributing to work-related musculoskeletal disorders (WMSDs) include awkward and static postures and repetitive movements. In agricultural operations, workers often adopt extreme bending, kneeling, squatting, or overhead postures due to varying crop heights, increasing stress on the musculoskeletal system. Repetitive tasks performed continuously at high frequency further increase fatigue and the likelihood of injury. Other important risk factors include manual material handling, force exertion, and vibration exposure. Frequent lifting and carrying of heavy loads place excessive strain on the back and upper limbs, while tasks requiring high force or the use of powered hand tools expose workers to vibrations that can damage muscles, tendons, and joints. Together, these factors significantly increase the risk of developing WMSDs in agricultural workers (Colim *et al.*, 2020; Koppelaar & Wells 2005; Luttmann *et al.*, 2003) [8, 25, 27].

Environmental Risk Factors

Environmental factors also contribute significantly to ergonomic risks in agriculture. Temperature extremes, uneven or unstable field conditions, poor lighting, and excessive noise can increase physical stress and reduce worker safety. Uneven terrain often forces workers to maintain unbalanced postures, while inadequate illumination affects task accuracy and increases the likelihood of accidents. These environmental conditions, combined with improper workplace or field design, can further elevate the risk of work-related musculoskeletal disorders (Clancy *et al.*, 2002; Cao *et al.*, 2019)^[4, 7].

Task-Specific Risk Factors

Ergonomic risks in agriculture vary with the working height and nature of the task. Under-knee activities such as weeding and transplanting in crops like strawberries, cucumbers, and tomatoes require prolonged bending and kneeling, leading to high musculoskeletal stress (Chandra *et al.*, 2021)^[6]. Waist-level operations involve frequent trunk bending and twisting, while above-shoulder harvesting of crops such as grapes, peaches, and pears places excessive strain on the shoulders and upper limbs. In addition, tasks such as pesticide spraying involve repetitive tool handling and load carrying, which further increase the risk of work-related musculoskeletal disorders (Hedge *et al.*, 1999; Luttmann *et al.*, 2003)^[19, 27].

Worker-Related Risk Factors

Individual characteristics also influence ergonomic risk in agricultural work. Age, gender, physical capacity, and work experience affect a worker's ability to safely perform physically demanding tasks. Older workers and those with lower physical strength are generally more susceptible to musculoskeletal disorders, as ergonomic risk increases when job demands exceed an individual's physical capacity. Additionally, experienced workers often adopt more efficient postures and work techniques than novices, resulting in differences in ergonomic risk during similar tasks (Takala *et al.*, 2010; Schaub *et al.*, 2013; Tuna & Colak 2025)^[36, 37, 38].

3. Classification of ergonomic risk assessment methods

3.1 Qualitative methods

Qualitative assessment methods, also referred to as self-assessment or self-report techniques, rely on workers providing information about their own experiences of physical stress and musculoskeletal symptoms. These techniques are generally inexpensive, require no technical equipment, and are highly suitable for large-scale assessments. While practical, these methods are inherently vulnerable to subjective bias and the fact that discomfort cannot be observed or measured directly by the evaluator (Hasheminejad *et al.*, 2021)^[18].

3.1.1 Worker feedback

Worker feedback involves the collection of data directly from subjects regarding their subjective experience of discomfort and pain. Workers often report a range of symptoms resulting from mechanical overload or repetitive tasks, including fatigue, stiffness, swelling, muscle strains, and tingling sensations. This feedback is essential for identifying early ergonomic risks and recognising an imbalance between workplace requirements and the worker's physical abilities (Chandra *et al.*, 2021; Das, 2023)^[6, 9]. Expert systems like SONEX are designed to relate these subjective symptoms and ergonomic shortcomings in the job to predict possible work-related musculoskeletal disorders (WRMSDs).

3.1.3 Interviews and Questionnaires

Standardised questionnaires and structured interviews are the primary tools for collecting qualitative ergonomic data. The standard nordic questionnaire (SNQ), or general nordic questionnaire, is considered a "gold standard" for determining the prevalence of musculoskeletal disorders. It typically consists of a demographic section followed by Yes/No questions regarding symptoms in specific body regions, such as the neck, shoulders, upper back, and lower back. Another widely used tool is the cornell musculoskeletal discomfort questionnaire (CMDQ), which assesses discomfort levels and their impact on work ability over the previous 7 days or 12 months (Kroemer 2008; Hasheminejad *et al.*, 2021; Das, 2023)^[9, 18, 26].

3.1.3 Discomfort and Pain Rating Scales

To provide a more structured form of feedback, workers use psychophysical rating scales to quantify their perceived effort. The borg CR-10 scale is a prominent tool where workers rate the muscular effort required for a task on a scale from 1 (very light) to 10 (greatest imaginable). These ratings allow evaluators to compare subjective perceptions of exertion with objective measures, such as muscle activity recorded through electromyography (EMG) (Bovenzi 2010; Chandra *et al.*, 2021)^[3, 6]. While there is sometimes a high correlation between these scales and worker discomfort, the definition of exertion variables can significantly affect the risk output of various assessment methods.

3.2 Semi-Quantitative Methods

Semi-quantitative methods bridge the gap between subjective worker reports and high-cost sensor measurements by assigning numerical values to physical stressors observed during work tasks. These methods are primarily posture-based scoring systems or observational checklists that allow for a quick, inexpensive, and systematic evaluation of workplace risk.

Several posture-based ergonomic assessment tools have been developed to evaluate musculoskeletal risk by analyzing deviations of body segments from neutral postures and assigning risk scores. Among these, rapid upper limb assessment (RULA) is one of the most widely used methods for assessing the upper limbs, neck, and trunk, producing a Grand Score ranging from 1 to 7, where higher scores indicate the need for immediate corrective action (McAtamney & Corlett, 1993; Hignett & McAtamney, 2000; Chandra *et al.*, 2021)^[6, 20, 30]. rapid entire body assessment (REBA) extends this approach by evaluating the entire body, including the legs and coupling factors, with scores ranging from 1 to 15 to classify risk into different action levels. More specialized assessment methods have also been developed for specific applications. Novel ergonomic postural assessment (NERPA) modifies the angular thresholds used in RULA to improve the identification of low-risk tasks and reduce overestimation of ergonomic risk. Agricultural upper-limb assessment (AULA) was specifically designed for agricultural operations and evaluates common upper-limb postures encountered during farming activities, classifying risk into four levels ranging from moderate to very high. postural ergonomic risk assessment (PERA) is intended for repetitive short-cycle tasks and combines posture, force, and task duration into a single score, providing a comprehensive evaluation of ergonomic risk for individual work cycles (Punnett & Wegman 2004; Hasheminejad *et al.*, 2021)^[18, 33].

Observational Checklists

Checklists provide a structured framework for identifying

specific ergonomic hazards related to tools, workstations, and environmental conditions. Several other ergonomic assessment tools have been developed for specific occupational settings and task characteristics. Ovako Working Posture Analysing System (OWAS) is one of the earliest observational methods, classifying the posture of the back, arms, legs, and handled load using a four-digit coding system. Although simple and quick to apply, its broad posture categories may not accurately capture complex working postures (Karhu *et al.*, 1977) [22]. Rapid Office Strain Assessment (ROSA) is designed specifically for computer-based office work, evaluating workstation components such as chair, monitor, keyboard, mouse, and telephone arrangement to identify ergonomic risks associated with prolonged computer use. Other checklist-based methods include PLIBEL (Plan för Identifiering av Belastningsfaktorer), which uses a simple yes/no questionnaire to identify musculoskeletal stress factors related to posture, tool design, and work organization (Chandra *et al.*, 2021) [6]. For highly repetitive tasks, the Strain Index (SI) and Occupational Repetitive Actions (OCRA) methods are widely used, as they emphasize the frequency, duration, and intensity of repetitive exertions to assess the risk of upper-limb musculoskeletal disorders more effectively than posture-based methods alone.

3.3 Quantitative methods

Quantitative methods in ergonomic risk assessment involve the use of instrument-based sensors attached to the worker's body to collect objective, high-accuracy data. These methods are often preferred in research contexts as they provide quantitative data that cannot be captured through human observation alone, such as the exact magnitude of force exerted (Chander & Cavatorta 2017; Akkeesuwana *et al.*, 2025) [1, 5].

3.3.1 Physiological Measurements

Physiological assessment focuses on the internal response of the human body to physical stressors, primarily through Electromyography (EMG). Surface Electromyography (sEMG): This is used to record the magnitude of muscle activity associated with both Maximum Voluntary Contraction (MVC) and job-simulated exertions. For example, in the sawmill industry, researchers use sEMG to evaluate the muscle activity of the flexor carpi radialis and ulnaris to determine the effort required to turn lumber or strike a hammer. Muscle Use Evaluation: In studies of smartphone users, sEMG is recommended to investigate specific muscle use in the neck region for various texting postures (Clancy *et al.*, 2002; Kee &

Karwowski 2006) [7, 23, 24].

3.3.2 Biomechanical Analysis

Biomechanical analysis applies the principles of classical mechanics to evaluate human movement and assess ergonomic risk by analyzing kinematic (motion) and kinetic (force) variables. Kinematic parameters such as displacement, velocity, and acceleration are measured using motion capture systems, including optical camera-based systems and non-optical wearable sensors such as accelerometers and gyroscopes (Hasheminejad *et al.*, 2021; Chandra *et al.*, 2021) [6, 18]. Joint movements are further quantified using instruments like electrogoniometers and inclinometers, while force plates and pressure sensors measure ground reaction forces and moments during different work activities. Biomechanical assessments also establish safe workload limits based on human physical capacity. The action limit (AL) for static force during an 8-hour workday is recommended as 3.2% of maximum voluntary contraction (MVC), representing a workload that most workers can perform without excessive risk. Studies have also reported significant gender differences in physical capacity, indicating that although most men can safely perform tasks at the Action Limit, comparatively fewer women possess the muscle strength required for workloads above the maximum permissible limit (MPL) (Jones & Kumar 2007; Karhu 1997) [21, 22].

4 Observational and Postural-Based Ergonomic Assessment Tools

4.1 Rapid Upper Limb Assessment (RULA)

The Rapid Upper Limb Assessment (RULA) is a widely accepted observational screening tool developed to evaluate exposure to work-related musculoskeletal disorder (WMSD) risk factors, particularly affecting the upper limbs, neck, trunk, and legs. As illustrated in Figure 2 (RULA hierarchical scheme), the assessment categorizes body segments into Group A (upper arms, lower arms, and wrists) and Group B (neck, trunk, and legs). Each body segment is assigned a posture score, which is subsequently combined with additional scores for muscle use and force/load to generate intermediate scores (C and D) (Schaub *et al.*, 2013; Ranavolo *et al.*, 2020) [35, 36]. These intermediate values are then integrated to produce a Grand Score ranging from 1 to 7, where higher scores indicate greater ergonomic risk and a more urgent need for corrective action. The interpretation of RULA, REBA, and PERA scores is summarized in Table 1.

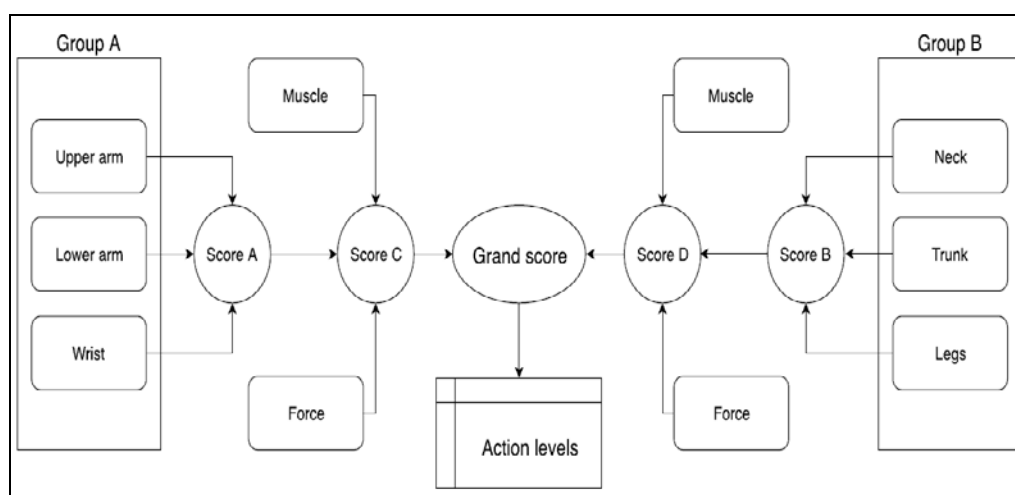


Fig 2: RULA hierarchical scheme

Table 1: Harmonized Risk Level Classifications

To compare tools, researchers often map their raw indices to three or four standard action levels.

Action Level	RULA Score	REBA Score	PERA Score	Risk Status
Level 1	1–2	0–1	< 4	Safe / Acceptable
Level 2	3–4	2–7	4–7	Possible Risk; Investigate
Level 3	5–6	8–10	> 7	High Risk; Change Soon
Level 4	7	11–15	> 14	Very High Risk; Change Now

The predictive validity of RULA is demonstrated in Table 2, where it achieved a 99% correct classification rate in high-risk sawmill jobs. Additionally,

Table 2: Predictive validity in high-risk industrial jobs

A study of high-risk sawmill jobs evaluated how correctly tools classified tasks known to be dangerous.

Tool used	Correct classification rate	Misclassification rate
RULA	99%	0%
Strain Index (SI)	97%	1%
REBA	64%	0%
OCRA (Borg Scale)	84%	2%
ACGIH TLV (%MVC)	3%	86%

Performance and Applications: RULA has demonstrated high predictive validity in industrial settings. In a study of high-risk sawmill jobs, RULA achieved a 99% correct classification rate for identifying at-risk tasks (McAtamney & Corlett, 1993)^[30]. It was also found to be the best predictor for the prevalence of musculoskeletal disorders in power plant repair tasks, specifically for the forearm, wrist, trunk, and neck. Furthermore, recent research identifies RULA as effective for assessing the high ergonomic risk of smartphone users, where 100% of participants in a texting study required further investigation or immediate change.

4.2 Rapid Entire Body Assessment (REBA)

The Rapid Entire Body Assessment (REBA) was developed as an advancement of RULA to provide a more comprehensive whole-body assessment and is particularly suitable for evaluating dynamic and unpredictable postures. REBA assesses the trunk, neck, legs, upper arms, lower arms, and wrists, allowing for 144 possible postural combinations while also incorporating additional factors such as coupling, load weight, and movement frequency (Hignett & McAtamney (2000; Das 2023)^[9, 20, 30]. The final REBA score ranges from 1 to 15 and is categorised into five ergonomic action levels requiring intervention. REBA has been reported to show a high correlation with subjective discomfort experienced by workers and has demonstrated better prediction of moderate risk levels in repair and maintenance occupations compared to RULA and NERPA. Additionally, its scoring system has shown a strong association with the prevalence of lower-limb musculoskeletal disorders. However, compared to RULA, REBA is often considered less sensitive to certain postural stresses and may underestimate postural load in some working conditions. Studies on sawmill job assessments reported that REBA correctly classified at-risk jobs in only 64% of cases, significantly lower than the 99% classification accuracy reported for RULA (Vitale *et al.*, 2024; Yazdanirad *et al.*, 2018)^[39, 40]. Similar to RULA, REBA also lacks duration analysis for cyclic tasks and may underestimate ergonomic risks associated with agricultural upper-limb postures.

4.3 Ovako Working Posture Analysis System (OWAS)

The Ovako Working Posture Analysing System (OWAS) is a practical ergonomic assessment method developed to evaluate whole-body postures in industrial and occupational settings. The

system categorises body positions using a four-digit coding structure representing the back, arms, legs, and the load handled, thereby enabling systematic posture evaluation (Parent *et al.*, 2012; Colim *et al.*, 2020)^[8, 31]. The method is widely applied for rapid assessment of physical workload and is particularly effective for instant analysis of single posture snapshots in workplace environments. Recent technological advancements have further enhanced OWAS applications through image-processing and machine-learning approaches that automatically identify postures from video streams using view-invariant features. Despite its practical advantages, OWAS has certain limitations because its posture categories are often broad and may not accurately represent complex or highly dynamic work activities (Halek *et al.*, 2005; Karwowski 2006; Dul 2003)^[12, 17, 23]. Studies have shown that OWAS and REBA are generally less sensitive to postural stress compared to RULA, frequently classifying tasks as low-risk that RULA identifies as moderate or high-risk. In agricultural ergonomics research, OWAS demonstrated an average hit rate of 34.4% when compared with expert evaluations, with a Cohen's kappa value of 0.538, indicating a moderate level of agreement.

4.4 Agricultural Upper-Limb Assessment (AULA)

The Agricultural Upper Limb Assessment (AULA) method was specifically developed to evaluate the physical workload experienced by farm workers by focusing on 14 upper-limb postures commonly observed during agricultural tasks. The method categories ergonomic risk into four levels, namely moderate, little high, high, and very high risk, with the highest level indicating the need for immediate ergonomic intervention. In agricultural ergonomics studies, AULA demonstrated a significantly higher agreement rate with expert evaluations compared to traditional industrial assessment methods, achieving 48.6% agreement, whereas RULA, REBA, and OWAS achieved agreement rates of 33.3%, 30.1%, and 34.4%, respectively. Accuracy is often measured by the "hit rate" (agreement with expert specialists is represented in table 3).

Furthermore, the method exhibited a Cohen's κ value of 0.718, indicating a good level of agreement with specialist ergonomists and suggesting that AULA is more suitable for farming-related posture assessments than conventional industrial ergonomic tools (Putz *et al.*, 1997; Bovenzi 2010; Jones & Kumar 2007.)^[3, 21, 33]. Despite these advantages, AULA has certain limitations because it primarily focuses on posture evaluation and does not

adequately account for load weight, which is a critical activities (figure 3).
ergonomic factor frequently encountered in agricultural

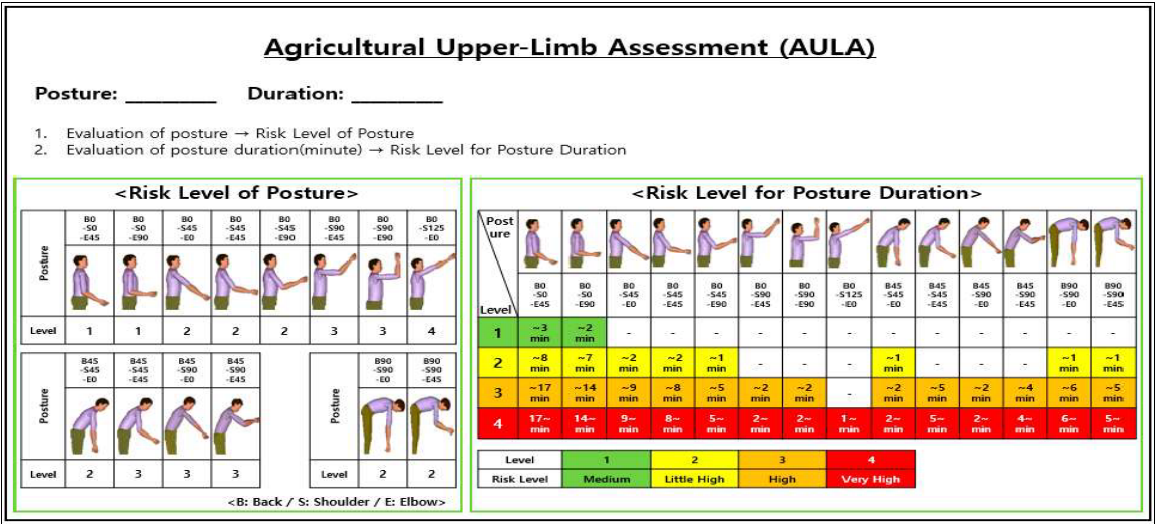


Fig 3: Agricultural Upper-Limb Assessment

Table 3: Performance Metrics: Reliability and Accuracy

Tool	Specialist Agreement (Hit Rate)	Cohen's Kappa (κ)	Strength of agreement
AULA	48.6%	0.718	Good
RULA	33.3%	0.599	Moderate
REBA	30.1%	0.578	Moderate
OWAS	34.4%	0.538	Moderate
AI-RULA (Computer Vision)	N/A	>0.60	Substantial

4.5 Postural Ergonomic Risk Assessment (PERA)

Postural Ergonomic Risk Assessment (PERA) is a simple observational ergonomic method developed to evaluate the postural risk associated with short cyclic assembly work. A unique feature of PERA is its ability to analyze every individual task within a work cycle separately, thereby enabling the identification of specific activities that contribute to higher ergonomic risk levels. The methodology is based on a multiplicative scoring model in which the score for each task is calculated using the relationship (Colim *et al.*, 2020; Ranavolo *et al.*, 2020) [8, 35].

Task Score = Posture × Force × Duration

This approach allows the simultaneous consideration of postural load, exerted force, and task duration in ergonomic risk

evaluation. The final overall work cycle score (A) is determined by averaging the scores of all tasks included within the work cycle, thereby providing a comprehensive representation of cumulative ergonomic exposure during repetitive work activities.

Risk Classification: A<4: Low Risk (Acceptable).
4≤A<7: Possible Risk (Further investigation needed).
A≥7: High Risk (Corrective action necessary).

Validation: PERA has achieved a 100% success rate in delivering the same risk evaluations as the European Assembly Worksheet (EAWS) for diverse assembly tasks. Table 4 shows that RULA had the highest correlation with WMSD prevalence in multiple body regions, particularly the neck (r = 0.812) and wrist (r = 0.739).

Table 4: Correlation with Musculoskeletal Disorder (WMSD) Prevalence

In repair and maintenance occupations, the following correlations were found between tool scores and actual self-reported discomfort levels.

Body Region	Best Predicting Tool	Correlation Coeff. (r)
Overall Disorders	RULA	0.764
Arm	NERPA	0.699
Forearm	RULA	0.728
Wrist	RULA	0.739
Trunk	RULA	0.632
Neck	RULA	0.812
Legs	REBA	0.699

4.6 Novel Ergonomic Postural Assessment (NERPA)

NERPA was developed as an improved version of the RULA method with the objective of enhancing the predictability of low-risk ergonomic conditions by refining and correcting the angular thresholds used in RULA assessments (Donisi *et al.*, 2022; Gallagher & Heberger 2013; Chander *et al.*, 2017) [5, 11, 13].

Similar to RULA, NERPA uses a final score range of 1 to 7 to categories ergonomic risk levels from low to very high risk. Comparative studies have indicated that NERPA is more effective in identifying low-risk tasks because it applies broader and more refined angular classifications. The ergonomic risk due to its narrower angular ranges of NEPRa, RULA and REBA

(Table 5) and stricter posture categorization criteria. Different tools assign "Low Risk" (neutral) status to different angular

ranges. NERPA was specifically developed to widen RULA's neutral zones to better identify low-risk tasks.

Table 5: Anatomical Sensitivity: Comparison of Angular Thresholds

Body Part	Movement	NERPA (Neutral)	RULA (Neutral)	REBA (Neutral)
Arm	Flexion/Extension	-20° to 20°	-20° to 20°	-20° to 20°
Forearm	Flexion	60° to 100°	60° to 100°	60° to 100°
Wrist	Flexion/Extension	0° to 15°	0°	0° to 15°
Trunk	Flexion	0° to 20°	0° to 20°	0° to 20°
Neck	Flexion	0° to 10°	0° to 10°	0° to 20°

NERPA: Novel Ergonomic Postural Assessment

RULA: Rapid Upper Limb Assessment

REBA: Rapid Entire Body Assessment

- **Weakness:** While it improved low-risk detection, the correction of angles in NERPA has reduced its ability to identify high and very high risks compared to the original RULA method.
- **Correlation:** It maintains a high correlation with RULA scores (approximately 0.72 to 0.76) in industrial settings.

4.7 LUBA

LUBA is an alternative posture-based assessment tool used to predict upper extremity musculoskeletal disorders. In

comparative effectiveness studies alongside RULA and NERPA, researchers found that RULA maintained a higher correlation with actual musculoskeletal disorder levels than LUBA. Despite this, LUBA remains a recognized method for evaluating physical states and conditions in specific industrial sectors. Based on the sources, observational ergonomic risk assessment tools - such as RULA, REBA, OWAS, and PERA are the most frequently used methods in industrial workplaces and the comparison of those are given in table 6. They offer significant practical advantages but are limited by subjective bias and a focus on static variables (Kee & Karwowski, 2006; Mazloui *et al.*, 2025) ^[23, 24, 29].

Table 6: General Comparison and Applications of Ergonomic Tools

Tool	Focus area	Score range	Primary industry/task application
RULA	Upper limbs, trunk, Neck	1–7	Industrial tasks, IT workstations, Repetitive hand work
REBA	Entire body	1–15	Healthcare, maintenance, dynamic tasks
AULA	Upper limbs	4 Levels	Agriculture (Harvesting, Weeding, etc.)
NERPA	Upper limbs	1–7	Manufacturing and assembly
ROSA	Office workstation	1–10	Computer-based office work, Call centres
PERA	Entire body	Multiplicative	Short cyclic assembly work
SI (Strain Index)	distalupper extremity	Index score	Repetitive hand work (e.g., meat packing, sawmills)
OWAS	Entire body	4 Categories	General industrial work, Forestry

Strengths of Observational Tools

- **Ease of Use and Implementation:** These tools are generally simple, flexible, and inexpensive to implement. They are designed to be conducted quickly, providing immediate results without requiring high-cost equipment.
- **Accessibility:** Most observational methods can be conducted by inexperienced users as the tools are easy to learn. They do not require the technical knowledge or costly sensors associated with direct measurement.
- **Non-Intrusiveness:** Unlike direct measurement methods that require attaching sensors to a worker's body, observational tools are non-intrusive and do not influence or limit the worker's natural movement.
- **Broad Scope:** Some tools, such as REBA, OWAS, and QEC, are designed to cover whole-body posture, providing a comprehensive view of physical stress across multiple joints.
- **Screening Utility:** They serve as excellent initial screening tools to identify high-risk tasks before deploying more technical or quantitative measurement systems.

Limitations of Observational Tools

Despite their widespread use, ergonomic assessment methods have several limitations. Most observational tools rely on the evaluator's judgment, making them susceptible to subjective bias and inconsistencies. Their accuracy can also be affected by poor lighting, camera occlusion, and unfavorable viewing angles. Additionally, many methods primarily assess static postures

while overlooking dynamic factors such as movement velocity, acceleration, and repetitive motions, which may lead to underestimation or overestimation of ergonomic risk in complex work environments. Furthermore, broad posture classification categories may not accurately represent complex body movements, and most conventional tools have limited capability to evaluate long-duration repetitive tasks or cumulative musculoskeletal loading (Ranavolo *et al.*, 2020; Mazloui & Kouhnavard 2025) ^[29, 35].

5. Physiological Assessment Methods

- **Heart rate measurement:** Heart rate measurement is a common physiological technique used to assess the cardiovascular load and overall physical strain placed on a worker during manual labour. It serves as an indicator of whole-body fatigue and can be used to establish structured work-rest schedules to prevent physical exhaustion (Grandjean & Kroemer, 1997; Karwowski, 2006; Cao *et al.*, 2019) ^[4, 15, 23, 26].
- **Energy expenditure:** Energy expenditure refers to the metabolic cost of performing a specific work task. In ergonomic research, measuring energy expenditure ensures that the physical demands of a job do not exceed a worker's long-term aerobic capacity, which helps mitigate the risk of systemic fatigue and secondary musculoskeletal (Ranavolo *et al.*, 2020; Madanagopal *et al.*, 2023) ^[35].
- **Oxygen consumption:** Oxygen consumption is an objective measure of work intensity. By measuring the rate at which a

worker consumes oxygen, ergonomists can determine the metabolic demands of industrial or agricultural tasks and evaluate the efficiency of different work methods or tool designs. (Outside Information) (Madeleine, 2010; Clancy *et al.*, 2002) ^[7, 28].

- **Electromyography (EMG):** Surface electromyography (EMG) is the primary physiological assessment method used to collect objective data on muscle activity during work tasks and Maximum Voluntary Contraction (MVC). EMG helps evaluate internal muscular effort during forceful activities such as hammering, which cannot be accurately assessed through visual observation alone (Putz *et al.*, 1997; Colim *et al.*, 2020) ^[8, 33]. Modern ergonomic tools such as the European Assembly Worksheet (EAWS) also integrate physiological and biomechanical assessment criteria for improved ergonomic evaluation. Physiological data obtained through EMG is further used to establish quantitative action limits for force, where an action limit of 3.2% MVC is considered acceptable for an 8-hour workday with minimal ergonomic risk (Koppelaar and Wells 2005)

- [25].
- **Noise and Vibration Assessment:** Ergonomic hazards identified by the National Institute for Occupational Safety and Health (NIOSH) include vibration as a major physical stressor that can contribute to musculoskeletal disorders and occupational injuries. Vibrations generated from powered hand tools are considered significant ergonomic risk factors, and in the PERA method, exposure to vibration is directly classified as a high-risk factor for force exertion. Prolonged exposure to vibration may result in occupational disorders such as vibration white finger, tendon inflammation, and neurovascular damage, particularly in occupations involving welding and milling activities (Kroemer 2008; Pheasant & Haslegrave 2018) ^[26, 32].
 - Strengths and Limitations of Physiological / Biomechanical (Direct) and Observational Methods (Comparison) are given in table 7 (Koppelaar. and Wells. 2005) ^[25].

Table 7: Strengths and Limitations

Feature	Physiological / Biomechanical (Direct)	Observational Methods (Comparison)
Accuracy	High accuracy; provides quantitative data.	Vulnerable to subjective bias.
Variables	Captures velocity, acceleration, and force.	Mostly focuses on static posture.
Worker Influence	Can be intrusive; may limit free movement.	Non-intrusive.
Resources	Requires expensive equipment and technical experts.	Inexpensive and easy to learn.
Data Context	Excellent for research and detailed job design.	Ideal for large-scale screenings

6. Digital and Sensor-Based Ergonomic Risk Assessment Methods

The transition from traditional observational methods to digital and sensor-based systems represents a significant shift in ergonomics, aiming to provide systematic, objective, and high-accuracy measurements of physical stress. These technologies utilize advanced hardware and machine learning to identify ergonomic deficiencies that may be invisible to the human eye, such as rapid changes in velocity or subtle muscle fatigue (Ranavolo *et al.*, 2020; Karwowski, 2006) ^[23, 35].

6.1. Variable Sensors

Direct measurement involves attaching electronic devices and anthropometric tools to a worker's body to collect quantitative data in real-time.

- **Kinematic and Postural Sensors:**
Wearable sensor technologies provide objective and continuous measurement of human movement for ergonomic assessment. Electrogoniometers accurately measure joint angles, particularly at the wrist and forearm, during repetitive tasks. Inertial measurement units (IMUs), which integrate accelerometers, gyroscopes, and magnetometers, enable real-time motion tracking even when body parts are obstructed from view (Clancy *et al.*, 2002; Vitale *et al.*, 2024) ^[7, 39]. Additionally, accelerometers measure body acceleration, providing valuable information on movement dynamics and muscle loading that is often overlooked by conventional posture-based assessment methods.
- **Physiological and Force Sensors**
Surface Electromyography (sEMG): Used to measure the magnitude of electrical activity in muscles associated with maximum voluntary contraction (%MVC). It is the "gold standard" for determining internal muscle loading during forceful tasks. (Force Plates and Pressure Sensors: Utilized

to calculate ground reaction forces and moments, or the pressure exerted during manual handling tasks (Madeleine, 2010; Bovenzi 2010) ^[3, 28].

6.2. Vision-Based Posture Analysis Systems

Vision-based assessment utilizes cameras and computer vision (CV) applications to automatically estimate human body models and joint angles.

Camera-Based Monitoring:

Computer vision-based motion analysis includes both marker-based and markerless systems for ergonomic assessment. Marker-based systems, such as vicon, use infrared cameras and reflective markers to achieve highly accurate motion capture but are generally limited to laboratory environments due to their high cost and limited portability (Colim *et al.*, 2020; Akkeesuwan *et al.*, 2025) ^[1, 8]. In contrast, markerless systems use RGB or RGB-D cameras to estimate body posture without wearable markers, making them more suitable for real workplace applications. Recent advances in openpose and other convolutional neural network (CNN)-based skeleton detection methods enable automatic tracking of multiple body joints from standard video, providing reliable posture analysis even under challenging conditions such as poor lighting, varying camera angles, and partial body occlusions.

6.3. IoT and cloud-based monitoring systems

The adoption of industry 4.0 technologies has enabled real-time and data-driven ergonomic assessment in workplaces. Wearable sensor networks, including inertial sensors and EMG devices, can continuously transmit movement data to cloud-based platforms for monitoring physical workload throughout a work shift. In addition, remote assessment systems allow experts to analyze field data through web-based platforms and provide instant ergonomic risk evaluations (Ranavolo *et al.*, 2020;

Chandra *et al.*, 2021; Das 2023)^[6, 9, 35]. By integrating posture data with production and logistics information, data fusion techniques further support the optimization of work methods and help reduce cumulative musculoskeletal stress on workers.

6.4 Artificial Intelligence and Machine Learning for Risk Reduction

Artificial intelligence (AI) and machine learning (ML) technologies are increasingly used in ergonomics to analyse complex datasets and support decision-making for ergonomic interventions. ML models can automatically calculate ergonomic risk scores such as RULA and OWAS by analysing body-joint positions obtained from video streams, and these automated assessments have shown strong agreement with expert evaluations. Expert systems such as SONEX utilise rule-based interfaces and extensive knowledge databases to associate workers' symptoms, including stiffness and tingling, with ergonomic risk factors in order to predict work-related musculoskeletal disorders (WRMSDs) and recommend preventive measures. AI-based predictive kinematic analysis also uses body acceleration and velocity data to estimate muscle force and internal stress, thereby assisting in establishing optimal work pace and reducing tissue degeneration risks. Furthermore, computer vision (CV)-based technologies can classify specific human activities and evaluate ergonomic risks based on the frequency and duration of tasks rather than posture alone (Mazloui & Kouhnavard 2025; Vitale *et al.*, 2024)^[29, 39].

7. Conclusion

Ergonomic risk assessment plays a crucial role in identifying work-related musculoskeletal disorder (WMSD) risks and improving the occupational health and safety of agricultural workers. Agriculture involves diverse manual operations characterized by repetitive movements, awkward postures, forceful exertions, prolonged working hours, and exposure to challenging environmental conditions, making workers highly susceptible to musculoskeletal disorders. Therefore, accurate and reliable ergonomic assessment methods are essential for evaluating occupational risks and designing effective interventions. This review highlights the evolution of ergonomic risk assessment methods from traditional observational techniques to advanced technology-assisted approaches. Conventional tools such as Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), Ovako Working Posture Analysis System (OWAS), Agricultural Upper Limb Assessment (AULA), and the recently developed Agricultural Ergonomics Risk Assessment (AERA) remain valuable because of their simplicity, cost-effectiveness, and ease of application in field conditions. However, these methods are often limited by observer subjectivity, time-consuming assessments, and reduced capability to evaluate dynamic agricultural tasks. Recent developments in wearable sensors, inertial measurement units, electromyography, computer vision, depth cameras, and artificial intelligence have significantly improved the objectivity, accuracy, and automation of ergonomic risk assessment. Machine learning and deep learning techniques have further enabled real-time posture recognition, continuous monitoring, and automatic risk prediction, thereby reducing human bias and increasing assessment efficiency. These technologies provide promising opportunities for precision ergonomics and intelligent occupational health monitoring in agriculture. Future research should focus on developing integrated ergonomic assessment frameworks that combine observational techniques with sensor-based

measurements, computer vision, and artificial intelligence to provide comprehensive, real-time, and field-applicable ergonomic evaluations. Greater emphasis should also be placed on validating these technologies across different agricultural operations, crops, climatic conditions, and worker populations. Such multidisciplinary approaches will contribute to more accurate risk identification, improved worker safety, enhanced productivity, and the sustainable development of agriculture. Overall, this review demonstrates that while conventional ergonomic assessment methods continue to serve as practical screening tools, emerging intelligent technologies represent the future of ergonomic risk assessment. Their successful integration into agricultural practices has the potential to substantially reduce musculoskeletal disorders, improve occupational well-being, and support the modernization of agricultural ergonomics.

8. Research Gaps

- a. Inconsistency and Lack of Consensus: There is currently little agreement regarding which physical exposures should be considered in a risk assessment and the relative role those variables play in causing musculoskeletal injuries (MSI). Different tools weight factors like repetition, force, and posture differently, leading to varying risk outputs for the same task.
- b. Neglect of Dynamic Variables: Most traditional ergonomic tools (e.g., RULA, REBA, OWAS) focus exclusively on static postures at a single point in time. They frequently neglect body acceleration and velocity, which are critical predictors of the force applied by muscles during movement ($F=ma$).
- c. Variable Definition Impact: There is a significant research gap regarding how to define exposure variables. Using peak posture versus average posture, or Borg scale (subjective) versus %MVC, significantly alters the risk scores of all assessed methods. Interaction of Risk Factors: There is limited epidemiological data to quantify the interactive effects between repetition, force, and posture. Most current models assume equal weights for these factors, which may not accurately reflect the physiological rate of tissue damage (Tuna & colak 2025; Mazloui & Kouhnavard 2025)^[29, 38].

9. Future Directions

Implementation of Kinetic and Kinematic Variables: Future ergonomic assessments should optimally use velocity and acceleration data to provide more reliable results. Acceleration data can serve as a benchmark to develop optimal work paces and accurately predict body net force exertion (Akkeesuan *et al.*, 2025; Tuna & colak 2025; Vitale 2024)^[1, 38, 39].

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