Study of Ergonomic Risk as a Predictor of Operational Inefficiency: Evidence from Vision-Based Monitoring in Rice Mills

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ABSTRACT

Rice milling exposes workers to repetitive lifting, bending, twisting, and upper-limb exertion, yet existing ergonomic assessment methods largely treat these postures as isolated events rather than cumulative production stresses. This study examines ergonomic risk as a predictor of operational inefficiency within vision-based monitoring environments. It first reinterprets RULA, REBA, and OWAS in computational terms. RULA is framed as a piecewise discrete additive function with high local sensitivity. REBA is presented as a coupled biomechanical matrix with stronger whole-body interaction logic. OWAS is treated as a finite-state classifier with coarse quantization and lower sensitivity. Across all three, the core limitation is the absence of temporal dynamics. They do not represent motion adaptation, exposure accumulation, or threshold-based fatigue progression. The study then proposes the Temporal Ergodic Score, TES, a time-integrated multi-model risk functional that combines frame-wise RULA, REBA, and OWAS scores and attenuates risk under active motion through angular velocity. Within this formulation, ergonomic exposure becomes a cumulative signal linked to throughput decline rather than a static compliance score. The manuscript argues that throughput remains stable until TES reaches a critical threshold, after which speed, coordination, accuracy, and output deteriorate. This reframing places ergonomics within production analysis and supports earlier intervention through continuous vision-based monitoring, targeted task rotation, and better workstation control in rice milling systems.

I. Introduction

Rice milling operations depend on cyclic manual tasks that include lifting, bending, twisting, and repetitive upper-limb movements, all of which embed biomechanical strain directly into production cycles. These physical demands mirror those documented across a range of manual industries where awkward postures, forceful exertions, and repetitive motions are recognized as primary contributors to musculoskeletal disorders (MSDs) (Winiarski et al., 2021; Kibria, 2023; Aswalekar & Tungikar, 2018). Ergonomic assessment tools such as the Rapid Upper Limb Assessment (RULA) and the Rapid Entire Body Assessment (REBA) have long been used to quantify postural risk in manufacturing, construction, and agricultural settings (Kibria, 2023; Lazăr et al., 2024; Petruse & Vlad, 2023; jafarvand et al., 2017), and these tools consistently reveal that tasks involving trunk bending, spinal twisting, and sustained upper-limb exertion place workers at elevated risk of injury (Hasheminejad et al., 2023; Aswalekar & Tungikar, 2018; Benos et al., 2020). The conventional framing of ergonomic risk treats it almost exclusively as a health outcome predictor, linking poor posture and repetitive strain to conditions such as low back pain, shoulder disorders, and upper-limb pathologies (Babangida et al., 2025; Medic-Pericevic et al., 2024; Singh, 2018; Collins et al., 2011). Studies in healthcare, agriculture, construction, and manufacturing have confirmed that bending, twisting, and static postures are strongly associated with MSD prevalence (Hasheminejad et al., 2023; Brinkmann et al., 2022; Pinzke & Lavesson, 2018; Aswalekar & Tungikar, 2018; Benos et al., 2020), and wearable sensor technologies now allow real-time biomechanical monitoring of these risk factors with increasing precision (Winiarski et al., 2021; Babangida et al., 2025; Conforti et al., 2020; Leggieri et al., 2023). Motion capture and inertial measurement unit (IMU) systems, for instance, have been deployed to quantify joint loads, trunk inclination, and limb kinematics during work, providing objective data on the magnitude and frequency of biomechanical exposures (Winiarski et al., 2021; Babangida et al., 2025; Lazăr et al., 2024; Conforti et al., 2020). What remains underexplored, and what this study addresses, is the operational consequence of ergonomic risk: its role in shaping throughput, cycle time, and production efficiency. Classical ergonomic models assume that risk is a function of instantaneous posture, expressed as:

$$E(t) = f(P(t))$$

Where P(t) denotes posture state and E(t) denotes ergonomic risk at time t (Winiarski et al., 2021; Kibria, 2023; Petruse & Vlad, 2023). This formulation is adequate for injury prediction but insufficient for understanding operational degradation, because fatigue and motion quality do not deteriorate instantaneously but accumulate over time through sustained exposure to biomechanical loads (Rout et al., 2019). Energy expenditure during repeated work cycles leads to progressive fatigue, and fatigue in turn degrades the speed, precision, and coordination of manual movements (Rout et al., 2019). The operational inefficiency I(t) at any given moment is therefore not a product of the posture adopted at that moment alone but rather a function of the temporally integrated ergonomic risk over the entire work period, expressed as

$$I(t) = \mathcal{F}\left(\int_0^t E\,(\tau)\,d\tau\right)$$

This distinction is critical. It means that ergonomic risk must be understood as a latent state variable, one that accumulates silently within production cycles and manifests as reduced throughput only after sufficient biomechanical strain has built up. Workstation design optimization research has recognized the need to combine ergonomic and operational objectives (Vilas et al., 2012), and some frameworks have attempted to link posture quality to productivity metrics (Mgbemena et al., 2020; Vilas et al., 2012), yet no study has formally modelled the temporal integration of ergonomic risk as a predictor of operational inefficiency in rice milling. Vision-based monitoring systems offer a pathway to bridge this gap, as camera-based posture tracking and machine-learning classification of movement patterns have demonstrated high accuracy in identifying correct and incorrect postures during manual material handling (Conforti et al., 2020; Leggieri et al., 2023). By deploying such systems in rice mills, it becomes possible to continuously estimate E(t) across full production shifts and to test the hypothesis that cumulative ergonomic exposure, rather than isolated postural snapshots, drives measurable losses in operational output. This study therefore reframes ergonomic risk from a purely occupational health concern to a production systems variable, positing that the temporal integral of biomechanical strain is a meaningful and measurable predictor of throughput loss in rice milling operations.

II. Methods

A. *Vision-Based Ergonomics: From Observation to Continuous Measurement*

1) *Digital Representation of Human Motion*

Traditional ergonomic assessment tools such as RULA, REBA, and OWAS have traditionally relied on manual observation by trained evaluators who visually inspect worker postures and assign risk scores, a process widely acknowledged as subjective and prone to low repeatability (Agostinelli et al., 2024; Huang et al., 2020; Rybnikár et al., 2022). The shift toward digital representation of human motion addresses these shortcomings by encoding the human body as a skeletal graph, where a set of key anatomical joints is tracked over time to produce coordinate pairs for each joint at every time step. Modern pose estimation frameworks, including OpenPose and convolutional pose machines, extract joint coordinates from standard RGB video feeds, enabling markerless, non-intrusive capture of worker postures in real operational settings (Li et al., 2020; Lin et al., 2022). Once the spatial coordinates of key joints are obtained, vector relationships between adjacent limb segments allow the computation of joint angles at each time instant through the inverse cosine of the dot product of the two segment vectors divided by the product of their magnitudes (Hossain et al., 2023; Li et al., 2016; Paudel et al., 2022). This mathematical formulation transforms what was previously a categorical, observer-dependent judgment into a continuous numerical signal grounded in measurable geometry. Several validation studies have confirmed that joint angles derived from vision-based systems show strong agreement with those obtained from gold-standard motion capture systems; for instance, Li et al. (2020) reported an average root mean square error of 4.77 degrees and an average Spearman correlation of 0.915 between their convolutional-pose-machine-based system and an optical motion capture reference across twelve distinct postures. Similarly, Zhang and Huang (2024) found an average root mean square error of 5.64 and an average Spearman correlation of 0.87 for eighteen postures when comparing their deep-learning-based Quick Capture Evaluation System against OptiTrack motion capture. Depth-sensor approaches using Microsoft Kinect have also been employed to track up to twenty skeletal coordinates in real time for ergonomic evaluation (Banga et al., 2022; Tee et al., 2017), though RGB-based 2D and 3D pose estimation methods are increasingly preferred in industrial contexts because they require only a single inexpensive camera and impose no physical burden on the worker (Agostinelli et al., 2024; Cruciata et al., 2025; Kwon et al., 2022). Paudel et al. (2022) demonstrated that 3D pose estimation from video sequences, combined with their body angle reliability decision method, achieved 93% accuracy for both RULA and REBA scores and 94% for OWAS when compared with expert ground truth for unoccluded postures. The capacity to represent the human body as a time-indexed skeletal graph, with continuously computed joint angles, fundamentally redefines ergonomic measurement: posture is no longer a snapshot captured at a single moment by a single observer but a dense, frame-by-frame digital record that supports rigorous time-series analysis (Agostinelli et al., 2024; Lin et al., 2022; Rybnikár et al., 2022).

2) *Continuous Ergonomic Signal Formation*

The availability of frame-level joint angle data makes it possible to compute ergonomic assessment scores not as isolated, one-time ratings but as continuous functions of time, where each established scoring model (RULA, REBA, or OWAS) is applied algorithmically at every captured frame to produce a temporally dense risk signal. Lin et al. (2022) developed an automatic real-time system that uses OpenPose-derived joint angles as input to a decision tree that selects the appropriate ergonomic assessment scale and computes REBA, RULA, or OWAS

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scores for every frame of an operation video, enabling the identification of peak-risk moments within an entire work cycle rather than relying on a single worst-case snapshot. Their system processed fifteen operation videos spanning six task types and reported the maximal score, risk level, and the number and percentage of frames classified as high risk across the full temporal extent of each task (Lin et al., 2022; Agostinelli et al., 2024), similarly validated a semi-automated, low-cost 2D RGB motion capture system for continuous posture monitoring across multiple manufacturing production lines, computing REBA and RULA scores on a frame-by-frame basis and reporting root mean square errors for both score magnitude and risk level classification relative to expert ratings. This continuous formulation means that for any work session, one obtains not a single RULA number, a single REBA number, or a single OWAS category, but three parallel time-series signals, each encoding the temporal evolution of ergonomic risk as assessed by its respective model (Agostinelli et al., 2024; Lin et al., 2022). Huang et al. (2020) demonstrated a comparable approach using wearable inertial sensors, where their automated system generated RULA and REBA scores at every time point during a task, with a graphical interface allowing users to scroll through the temporal signal and locate the moment of maximum risk via a dedicated function, achieving intraclass correlation coefficients of 0.83 or higher and classification accuracies above 88% against expert ratings. Hossain et al. (2023) extended this logic by training a deep neural network on 3D keypoints from the Human3.6M dataset to predict REBA risk levels for each body configuration, achieving 89.07% accuracy on a test set of over 128,000 samples, thereby enabling automated, continuous risk prediction at scale. The practical consequence of treating RULA, REBA, and OWAS outputs as continuous signals rather than discrete observations is substantial: it permits the detection of cumulative exposure patterns, the identification of transient high-risk postures that episodic observation would miss, and the statistical correlation of ergonomic risk trajectories with operational performance metrics over time (Rybnikár et al., 2022; Agostinelli et al., 2024; Lin et al., 2022; Cruciata et al., 2025). Taken together, these advances establish that vision-based ergonomic monitoring produces rich, temporally resolved risk signals that open the door to treating ergonomic exposure as a quantitative predictor variable in models of operational efficiency, rather than a static compliance metric assessed at infrequent intervals.

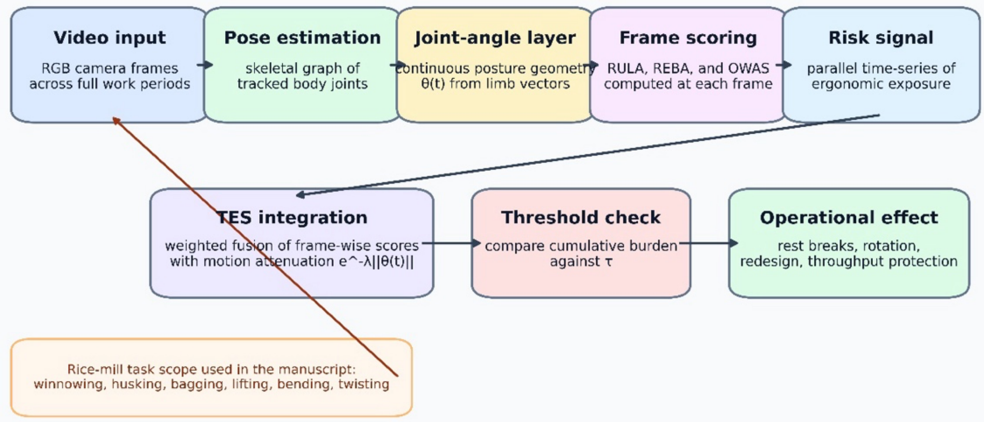

Fig. 1. Vision-based ergonomic pipeline

Figure 1 translates the stated pipeline from vision-based observation into operational consequence. It starts with RGB video capture, passes through pose estimation, joint-angle extraction, frame-wise RULA/REBA/OWAS scoring, and continuous risk-signal formation, then ends at TES integration, threshold checking, and operational intervention linked to throughput protection in rice-mill tasks.

III. Results and Discussion

A. *Computational Reinterpretation of Classical Models*

1) RULA as a Piecewise Discrete Function

RULA operates as a scoring system that sums discrete components representing upper limb posture, trunk and neck posture, muscle use, and applied force, expressed as

$$E_{RULA}(t) = A(t) + B(t) + M(t) + F(t)$$

The method was originally designed to identify external loads applied to the upper arms, forearms, wrists, trunk, neck, and legs, along with grip force and work frequency (Hay et al., 2019). In computational terms, each component function maps a continuous joint angle to a discrete integer score through predefined angular thresholds, making the overall function piecewise and discontinuous. Multiple comparative studies have confirmed that RULA exhibits the highest sensitivity among common observational tools, particularly for tasks involving substantial upper limb movement (Fathimahhayati et al., 2021; Landekić et al., 2019). This heightened sensitivity means that small changes in wrist or forearm angle produce disproportionately large score changes relative to equivalent angular shifts in the trunk, yielding a steep partial derivative $\frac{\partial E}{\partial \theta_{wrist}}$ that far exceeds $\frac{\partial E}{\partial \theta_{trunk}}$. Systematic comparisons across forestry, rubber tapping, and chassis assembly tasks consistently show that RULA rates postural loads at higher risk levels than either REBA or OWAS (Kusmindari et al., 2022; Pratiwi et al., 2019; Yovi & Wilantara, 2023). Kusmindari et al. (2022) reported that in 30 out of 36 studies comparing RULA and REBA, RULA estimated postural loads more stressfully. This tendency toward elevated scores reflects the steep sensitivity gradients embedded in its scoring architecture. A critical computational limitation, noted by Hay et al. (2019), is that RULA, as a qualitative method requiring professional observers, has certain limitations in dynamic posture analysis. The scoring function contains no dependence on time derivatives θ(t), meaning it treats a rapidly changing posture identically to a static one held at the same angle. The method evaluates only the instantaneous angular configuration at a single time point, ignoring velocity and acceleration of joint movement entirely (Kusmindari et al., 2022; Paudel et al., 2022).

2) REBA as a Coupled Biomechanical System

REBA extends the assessment framework beyond simple additive scoring by introducing a lookup matrix $g(\cdot)$ that couple's upper body (Group A) and lower body (Group B) scores, with additional terms for coupling quality and activity type, expressed as

$$E_{REBA}(t) = g(A(t), B(t)) + C(t)$$

Unlike RULA, which was developed primarily for upper limb assessment, REBA was designed as a postural analysis system sensitive to musculoskeletal risks across a variety of tasks, especially in healthcare and service industries (Kusmindari et al., 2022). The lookup matrix creates interdependence between body segment scores, so the partial derivative of the final score with respect to one joint angle θ_i is not independent of another joint angle θ_j. This coupled structure means that the same trunk flexion angle produces different final scores depending on the concurrent leg posture, a property confirmed by studies showing that REBA captures whole-body postural interactions that RULA misses in lower limb assessment (Fathimahhayati et al., 2021; Nelfiyanti et al., 2022). REBA also incorporates two additional assessment factors, coupling and dynamic loading effects, that RULA lacks (Kusmindari et al., 2022). Comparative field studies in forestry operations found that REBA produced sharper risk categorizations than OWAS across all machine types evaluated (Pratiwi et al., 2019), while in rubber tapping, REBA rated certain postures as medium risk where OWAS found no action required (Fathimahhayati et al., 2021). The inter-rater reliability of REBA observations has been reported at 93% for intra-rater and 54% for inter-rater assessments (Hida et al., 2022), suggesting variability in how different observers interpret the coupled scoring tables. The fundamental computational limitation of REBA is its assumption of quasi-static posture over the observation interval Δt. The method captures a snapshot of body configuration and processes it through the coupling matrix, but it does not account for how rapidly the worker transitioned into or out of that posture (Hay et al., 2019; Kusmindari et al., 2022). This static assumption restricts REBA from modeling the biomechanical consequences of dynamic, repetitive, or transitional movements common in manual labor settings.

3) OWAS as a Finite-State System

OWAS operates as a finite-state classification system that maps observed body configurations into one of four discrete action categories, expressed as $E_{OWAS}(t) \in \{1,2,3,4\}$, where each category indicates the urgency of corrective intervention (Gu et al., 2025; Liu et al., 2024). The method classifies postures based on categorical states of the back (4 positions), arms (3 positions), legs (7 positions), and load handled (3 categories), producing up to 252 possible combinations (Kee, 2022; Varghese et al., 2025). Computationally, this classification functions as a quantization operator Q applied to the continuous posture space $P(t)$, yielding $E_{OWAS}(t) = Q(P(t))$. The coarse granularity of this quantization introduces substantial quantization error $\epsilon_q = \mid E_{true} - E_{OWAS} \mid$, a problem documented across multiple domains. Yovi and Wilantara Fathimahhayati et al. (2021) demonstrated that OWAS has a very low level of sensitivity when applied to pine tapping activities, failing to flag postures that RULA and REBA identified as high or extremely high risk. Can, (2018) found no significant correlation between OWAS action categories and deltoid muscle activity measured by electromyography, concluding that OWAS appears inappropriate for representing workload of the shoulder and arm region. Kajaks et al., 2023) acknowledged that OWAS uses minimal and general posture categories with broad bin definitions and limited load exposure factors. Kusmindari et al. (2022) confirmed that OWAS generally evaluates postural loads as the least stressful among the three methods, with agreement rates between OWAS and RULA being lower than those between RULA and REBA. Gómez-Galán et al. (2019) reported that for higher action categories, OWAS highlights significantly fewer postures compared to REBA. The broad categorical bins that define OWAS sacrifice resolution for simplicity, making the method fast and easy to deploy (Gu et al., 2025; Gómez-

Galán et al., 2017) but prone to underestimating risk in tasks requiring fine postural discrimination.

4) Comparative Limitation: Absence of Temporal Dynamics

All three classical models, RULA, REBA, and OWAS, share a fundamental computational deficiency: none incorporates the time derivative of joint angles $\dot{\theta}(t) = \frac{d\theta}{dt}$, which governs the velocity and adaptive motion behavior of workers during task execution. Hay et al. (2019) explicitly noted that current OWAS and RULA methods have limitations in dynamic posture analysis, and when the number of key postures requiring manual analysis is considerable, the efficiency of these methods decreases. Each method evaluates posture at discrete time points or over brief observation windows without modeling how postures evolve, transition, or accumulate fatigue over continuous work cycles (Kusmindari et al., 2022; Can, 2018). This absence of temporal dynamics means that a worker who holds a moderately risky posture for an extended duration receives the same score as one who passes through it briefly during a transition. Kusmindari et al. (2022) noted that while RULA and REBA evaluate repeated and static posture effects through additive score adjustments, these adjustments are binary flags rather than continuous functions of exposure duration or movement velocity. The OWAS method, despite being applied with time-sampling protocols where video records are stopped at fixed intervals to increase observational sensitivity (Hussain et al., 2016) still produces only a sequence of independent snapshots rather than a temporally coherent trajectory. The vector field $\theta, \dot{\theta}, \ddot{\theta}$ that would fully describe the dynamics of postural change remains absent from all three assessment frameworks, leaving a gap that limits their capacity to predict cumulative musculoskeletal risk in repetitive, time-varying occupational tasks such as those found in rice milling operations.

Table 1. Classical Ergonomic Models and TES: Comparative Computational Reading

Model	Manuscript formal representation	Mathematical structure	Sensitivity to posture variation	Temporal treatment	Main computational limitation	Operational meaning in manuscript
RULA	E_RULA(t) = A(t) + B(t) + M(t) + F(t)	Piecewise discrete additive score assembled from posture, muscle use, and force components.	Highest local sensitivity; small wrist or forearm changes can produce large score shifts; manuscript notes RULA rated risk higher in 30 of 36 RULA–REBA comparisons.	No explicit dependence on $\dot{\theta}(t)$; evaluates instantaneous angular configuration only.	Rapidly changing and static postures at the same angle receive the same score; dynamic accumulation is absent.	Useful for acute posture discrimination, especially upper-limb loading, but insufficient on its own for throughput degradation prediction.
REBA	E_REBA(t) = g(A(t), B(t)) + C(t)	Coupled biomechanical matrix linking upper- and lower-body groups with additional activity/coupling terms.	Captures inter-segment dependence better than RULA; the same trunk posture can score differently under different leg postures.	Quasi-static snapshot model; no transition speed or continuous exposure accumulation.	Cannot represent repetitive or transitional movement consequences over time.	Improves whole-body interaction capture, yet still remains a posture snapshot rather than an operational fatigue model.
OWAS	E_OWAS(t) = Q(P(t)), with E_OWAS(t) ∈ {1,2,3,4}	Finite-state classifier created by coarse quantization of posture states.	Lowest sensitivity among the three classical tools; broad categories sacrifice fine discrimination.	Sequence of independent sampled states; no temporally coherent trajectory.	Quantization loss and under-detection of fine postural differences, especially shoulder/arm workload.	Fast general overview tool, but too coarse by itself for predicting operational inefficiency in repetitive rice-mill tasks.
TES	TES = ∫[αE_RULA(t) + βE_REBA(t) + γE_OWAS(t)] e^-λ‖$\dot{\theta}$(t)‖ dt	Time-integrated multi-model risk-energy functional with motion attenuation.	Uses complementary sensitivities of RULA, REBA, and OWAS instead of inheriting only one method's bias.	Explicitly temporal: integrates exposure over T and discounts active motion through angular velocity.	Requires calibration of α, β, γ, λ, τ, and k from field data.	Transforms ergonomic risk from a static compliance score into a predictor of threshold-driven throughput loss.

Table 1 compares RULA, REBA, OWAS, and TES strictly on the computational terms emphasized in the manuscript: formal representation, mathematical structure, sensitivity behavior, temporal treatment, core limitations, and operational meaning. It preserves the manuscript's central claim that TES resolves the temporal deficiency shared by the three classical models.

B. *Temporal Dynamics and the Emergence of Inefficiency*

1) Ergonomic Risk as a Time-Dependent Function

Classical ergonomic assessment tools such as RULA, REBA, and OWAS produce discrete scores at isolated time points, treating each observation as independent of what came before or after (Kee, 2022). In practice, the cumulative effect of sustained or repeated postural loading over a work shift matters far more than any single snapshot. Redefining ergonomic exposure as a time-dependent functional, $\mathcal{E}(T) = \int_0^T E(t)\,dt$, captures the total postural burden a worker accumulates across the observation window T. This integral formulation reflects what multiple field studies have observed: workers who maintain moderate-risk postures for extended durations develop musculoskeletal complaints at rates comparable to those in high-risk postures held briefly (Hay et al., 2019; Yovi & Wilantara, 2023). Hay et al. (2019) found that physical therapists who stood for long periods showed strong correlations between sustained posture and lower back pain (r = 0.84), a finding that a single-frame OWAS score would fail to represent. Savin et al. (2021) demonstrated that fatigue-induced movement variability appeared early in a repetitive pointing task and evolved continuously over time, confirming that human motion introduces adaptation, meaning $\dot{\theta}(t) \neq 0$ it triggers fatigue modulation that alters the effective risk profile as the task progresses. The absence of this temporal integration in standard tools means that two workers with identical instantaneous RULA or REBA scores but different exposure durations receive the same risk classification, a limitation that Kee (2022) and Lorenzini et al. (2023) both identified as a core deficiency of observational methods. Recasting ergonomic risk as a functional over time provides the mathematical foundation needed to link postural exposure to the gradual degradation of worker performance in repetitive manual operations such as those found in rice milling.

2) Adaptive Motion and Fatigue Delay

Workers do not hold static postures passively. They adapt their movement patterns in response to discomfort and developing fatigue, a phenomenon that standard ergonomic tools ignore entirely (Lorenzini et al., 2023; Savin et al., 2021). Savin et al. (2021) showed that during a repetitive upper limb task performed to exhaustion, subjects exhibited measurable kinematic adaptations from as early as 65% of the total task completion time, with individual movement cycles deviating progressively from initial patterns. This adaptive behaviour acts as a dynamic attenuation factor on effective risk. When a worker moves fluidly between postures, the brief transit through a high-risk configuration imposes less musculoskeletal load than a prolonged static hold at the same joint angle. Introducing a dynamic attenuation factor $\phi(t) = e^{-\lambda\|\dot{\theta}(t)\|}$ formalizes this relationship: high angular velocity (active motion) reduces the effective instantaneous risk, while static posture ($\dot{\theta} \approx 0$) amplifies it. Brambilla et al. (2023) confirmed through electromyography studies that significant biomechanical and physiological changes occur in fatigued muscles, and that kinematic changes during long-duration manual tasks serve as detectable indicators of fatigue onset. Lorenzini et al. (2023) noted that the dynamics of tasks are considered to a limited extent in observational methods, with interaction forces treated as constant. Baklouti et al. (2024) reported that their IMU-based system detected a higher occurrence of postures warranting investigation that traditional RULA assessments missed, precisely because the wearable system captured continuous motion data rather than discrete snapshots. In rice milling, where workers perform repetitive lifting, bending, and carrying tasks across multi-hour shifts, this adaptive motion behavior creates a delay between the onset of biomechanical stress and the point at which fatigue overwhelms the worker's compensatory strategies, a delay that no classical scoring method accounts for.

3) Inefficiency as a Threshold Process

Throughput degradation in manual labor settings does not occur linearly with increasing ergonomic risk. Instead, it follows a threshold process: operational performance remains relatively stable until cumulative ergonomic exposure $\mathcal{E}(T)$ exceeds a critical value τ, after which output drops sharply. Digiesi et al. (2018) formalized this concept in assembly line contexts by defining individual ergonomic risk thresholds beyond which worker productivity declines, and they developed optimization models that maintain cumulative RULA scores below acceptable limits to preserve production targets. Quiroz-Flores et al. (2023) documented that in a plastics manufacturing plant, high postural loads at workstations directly generated absenteeism, and reducing RULA and REBA risk levels by 50% to 66.7% produced annual savings of 42,929 PEN in absenteeism-related costs, demonstrating a clear threshold relationship between ergonomic exposure and operational loss. Brito et al. (2018) showed in a metallurgical industry case study that ergonomic interventions targeting high-risk postures improved both working conditions and productivity simultaneously, confirming that crossing the risk threshold degrades output while staying below it preserves it. Savin et al. (2021) provided biomechanical evidence for this threshold by showing that fatigue-induced movement variability, once triggered, altered joint angle trajectories enough to change RULA score classifications during the same task. Trost et al. (2022) reviewed production planning literature and found that models incorporating ergonomic risk thresholds into scheduling decisions achieved better balance between output targets and worker health outcomes. In rice milling operations, where workers perform physically demanding tasks across extended shifts with minimal mechanization, the threshold model predicts that cumulative postural stress will reach a tipping point during the work period, after which task completion rates, accuracy, and throughput all decline. Identifying this threshold τ through vision-based monitoring systems offers a practical mechanism for triggering rest breaks or task rotations before inefficiency sets in.

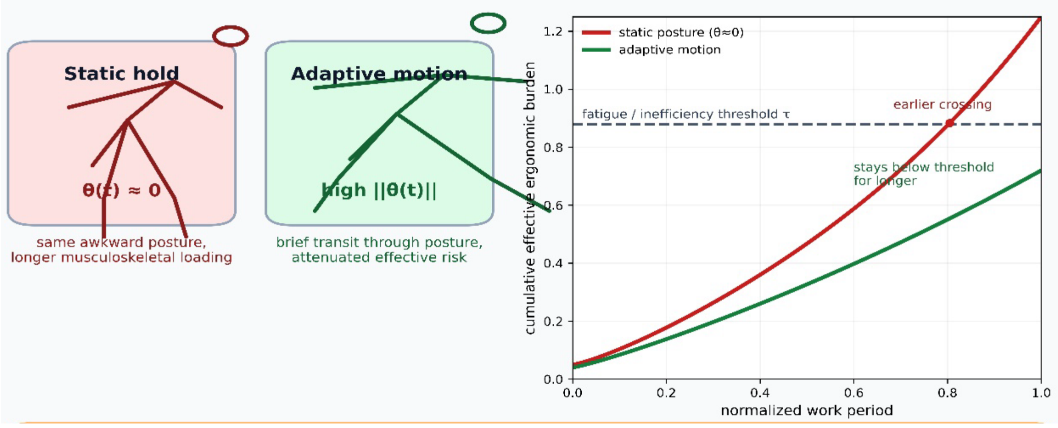

Fig. 2. Static vs dynamic posture accumulation curves showing divergence in fatigue buildup.

Figure 2 operationalizes the study's distinction between static holding and adaptive motion. The left side contrasts posture states using angular-velocity logic, while the right side shows cumulative burden diverging over the normalized work period, with static posture crossing the fatigue or inefficiency threshold earlier than dynamic motion.

C. *Temporal Ergodic Score (TES): A Unified Model*

1) *TES Formulation*

The Temporal Ergodic Score (TES) addresses the core limitation shared by RULA, REBA, and OWAS: their inability to account for cumulative, time-varying postural exposure in a single unified metric. The proposed formulation is

$$TES = \int_0^T [\alpha E_{RULA}(t) + \beta E_{REBA}(t) + \gamma E_{OWAS}(t)] \cdot e^{-\lambda \|\dot{\theta}(t)\|} dt,$$

where $\alpha, \beta, and\, \gamma$ are weighting coefficients that reflect the relative contribution of each assessment method, and λ is a dynamic attenuation constant governing the discount applied to active motion. This multi-model integration responds directly to findings by Kee (2022), who demonstrated that RULA, REBA, and OWAS produce systematically different risk ratings for the same tasks, with RULA assessing postural loads as higher risk in 30 out of 36 comparative studies. Varghese et al. (2025) confirmed that each method has distinct strengths: OWAS provides a general overview, RULA captures upper limb demands, REBA assesses whole-body postures, and no single tool is sufficient on its own. By weighting and summing all three scores at each time step, TES draws on the complementary sensitivities of each method rather than relying on any one alone. The exponential attenuation term $e^{-\lambda \|\dot{\theta}(t)\|} dt$ incorporates the dynamic motion behaviour that Lorenzini et al. (2023) identified as absent from standard observational tools, and that Savin et al. (2021) showed modulates fatigue onset during repetitive tasks. Menezes et al. (2022) demonstrated in a metallurgical electrolysis unit that exposure time quantification is essential for determining the criticality of musculoskeletal stress, reinforcing the need for a time-integrated formulation. The continuous integral over the observation window T transforms discrete, snapshot-based scores into a cumulative risk-energy quantity that reflects the total postural burden a worker absorbs during a shift.

2) *Interpretation*

TES functions as a risk-energy functional that accumulates strain over time, discounts adaptive motion, and integrates perspectives from multiple ergonomic models into a single scalar output. The accumulation property addresses what Hanson et al. (2018) described as the load dose concept, where exposure is quantified in terms of intensity, frequency, and duration, and the accumulated dose is employed for assessing dose-response relationships with musculoskeletal disorders. The dynamic attenuation component ensures that a worker who moves fluidly through a high-risk posture receives a lower TES increment than one who holds the same posture statically, consistent with the physiological evidence from Brambilla et al. (2023) showing that static muscle contraction restricts blood flow and accelerates fatigue more than dynamic loading. Yamamoto (1997) noted that static postures cause disturbance of peripheral circulation by compressing blood vessels, easily causing muscle fatigue, while dynamic postures facilitate blood circulation through muscular pump action. This distinction is encoded directly in the attenuation factor. The multi-model integration within TES also resolves the disagreement problem documented by Nelfiyanti et al. (2022), who found that OWAS, RULA, and REBA produced the same risk category in only 83.33% of chassis assembly working groups, diverging on the remaining cases. By combining all three scores with calibrated weights, TES produces a consensus measure that is less sensitive to the idiosyncratic biases of any individual tool. A high TES value at the end of a work period signals that the worker has accumulated substantial postural strain that was not adequately offset by adaptive movement, providing a direct indicator of musculoskeletal overload risk.

3) Vision-Based Implementation

Implementing TES in practice requires a computational pipeline that extracts pose data from video, computes joint angles, generates frame-wise ergonomic scores, estimates angular velocities, and performs numerical integration. Paudel et al. (2022) demonstrated that 3D human pose estimation from video sequences achieves over 90% accuracy in replicating OWAS, REBA, and RULA scores, establishing the feasibility of automated, frame-level scoring from standard RGB cameras. Cruciata et al. (2025) advanced this approach with a lightweight Vision Transformer that classifies ergonomic risk at the frame level directly from raw RGB images, achieving F1-scores exceeding 0.99 across all anatomical regions assessed, without requiring skeleton reconstruction or joint angle estimation as intermediate steps. Wang et al. (2023) proposed a non-invasive method using 3D pose recognition to extract joint coordinates and angles, then applied fuzzy logic to the REBA method to capture slow transition features of continuous human movement without abruptly altering risk scores, reporting a correlation coefficient of 0.817 ($p < 0.01$) with standard REBA. Hida et al. (2022) showed that two-dimensional joint coordinates extracted from work images, combined with support vector machine models, achieved over 80% agreement with OWAS action categories. For TES computation, the discrete approximation $TES \approx \sum_{t=1}^{T} (\alpha E_R + \beta E_B + \gamma E_O)\, e^{-\lambda \|\dot{\theta}_t\|} \Delta t$ is applied frame by frame, where angular velocity θ(t) is estimated from consecutive frame joint angle differences divided by the inter-frame time interval Δt. Safari et al. (2025) confirmed that computer vision combined with AI algorithms represents a current research trend for predicting musculoskeletal disorder risks, improving efficiency and accuracy compared to traditional observational methods. Baklouti et al. (2024) validated that continuous sensor-based monitoring detects a higher occurrence of postures warranting investigation than traditional snapshot methods like RULA, supporting the value of frame-wise scoring and integration over time.

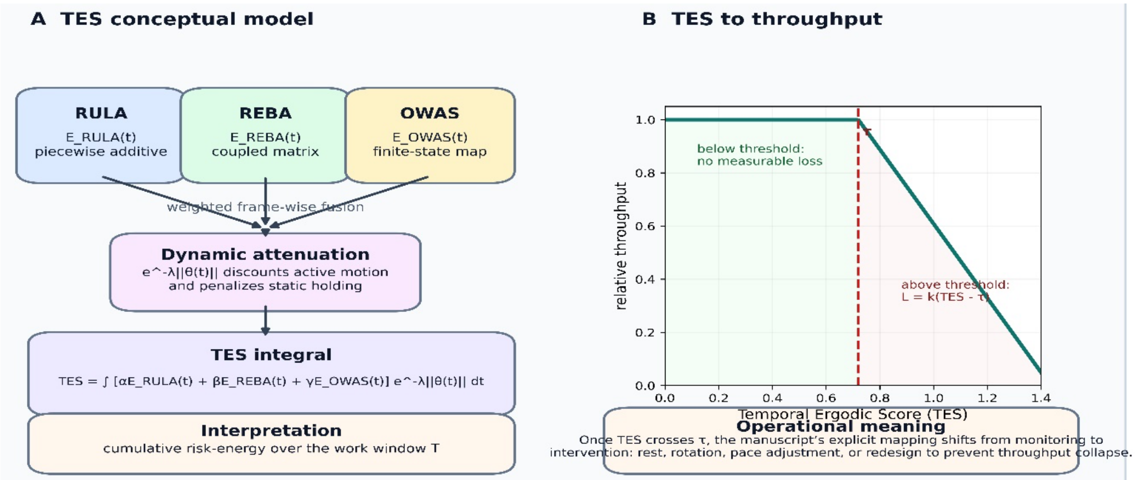

Fig. 3. TES vs throughput showing nonlinear degradation beyond threshold.

Figure 3 integrates the study's TES formulation and its throughput mapping in one coherent visual. Panel A shows weighted fusion of RULA, REBA, and OWAS with dynamic attenuation and time integration; Panel B shows the threshold-mediated throughput response, where performance remains stable below τ and degrades once TES exceeds it.

4) Mapping TES to Throughput Loss

The relationship between accumulated ergonomic risk and operational output follows a threshold-linear model defined as $L = k(TES - \tau), TES > \tau$, where L represents throughput loss, k is a scaling constant, and τ is the critical TES threshold below which no measurable performance degradation occurs. Digiesi et al. Digiesi et al. (2018) formalized this type of relationship in assembly line contexts by defining individual ergonomic risk thresholds and developing optimization models that maintain cumulative RULA scores below acceptable limits to preserve production targets. Menezes et al. (2022) documented in a metallurgical electrolysis unit that increased deformities in copper cathodes corresponded with increased on-time activities requiring awkward postures, linking postural overload directly to production losses and worker discomfort. Brito et al. (2018) showed that ergonomic interventions targeting high-risk postures in a metallurgical industry improved both working conditions and productivity simultaneously, confirming that the relationship between risk and output is bidirectional: reducing risk below the threshold restores throughput. Kahya and Şahin (2019) demonstrated that incorporating ergonomic risk scores into assembly line balancing improved total line performance by 7.41%,

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providing a concrete example of how managing cumulative ergonomic exposure translates into measurable operational gains. The scaling constant k in the TES-throughput model is task-specific and must be calibrated from field data in the target environment. In rice milling operations, where workers perform repetitive lifting, carrying, and bending tasks across extended shifts, the threshold τ and scaling constant k together define the operational window within which management interventions, such as rest breaks, task rotations, or workstation redesign, must be triggered to prevent throughput collapse.

Table 2. Mapping Cumulative Ergonomic Risk to Throughput Behavior

Risk / exposure regime	**Manuscript condition**	**Ergonomic interpretation**	**Fatigue / adaptation state**	**Expected throughput behaviour**	**Recommended operational response**	**Precision note**
Instantaneous posture only	$E(t) = f(P(t))$ without temporal integration	A single posture snapshot indicates momentary risk but not cumulative burden.	Adaptation history is invisible; duration and motion quality are not represented.	Insufficient by itself for explaining operational degradation.	Use only as an input layer for continuous monitoring.	This is the manuscript's starting limitation, not its final predictive model.
Low cumulative burden	TES below τ; cumulative exposure remains under the critical threshold.	Postural strain exists but is still bounded within the worker's current compensatory capacity.	Adaptive motion still attenuates effective risk.	No measurable throughput loss is expected.	Continue monitoring and preserve current work rhythm.	The manuscript defines this regime symbolically, not numerically.
Approaching threshold	TES approaches τ.	Cumulative burden is rising toward the tipping point where inefficiency can emerge.	Fatigue delay is narrowing; movement variability is likely increasing.	Throughput can remain stable but becomes vulnerable to a sharp drop.	Prepare a break, task rotation, pace reduction, or workstation correction.	This row converts the manuscript's threshold logic into a pre-intervention state.
Threshold exceeded	TES > τ and $L = k(TES - τ)$.	Critical burden has been exceeded; risk becomes operationally consequential.	Compensatory strategies are no longer offsetting the accumulated load.	Throughput loss begins and increases with further TES growth.	Trigger intervention immediately.	This is the explicit mapping given in Section 5.4.
Sustained exceedance	TES remains above τ across the work window.	Prolonged overload state with continued postural strain accumulation.	Fatigue dominates; coordination, speed, and accuracy degrade.	Task completion rate, throughput, and accuracy decline together.	Redesign task mix, pace, workstation, or staffing pattern.	The manuscript links this state to rest scheduling, rotation, and redesign in smart rice milling.

Table 2 maps cumulative ergonomic exposure to throughput behavior using the manuscript's symbolic threshold logic rather than invented calibration values. It distinguishes instantaneous posture assessment, low cumulative burden, threshold approach, threshold exceedance, and sustained exceedance, then ties each regime to fatigue state, throughput behavior, and operational response.

D. Implications for Smart Rice Milling Systems

1) Real-Time Ergonomic Intelligence

The Temporal Ergodic Score (TES) framework, when deployed through vision-based monitoring, enables continuous ergonomic surveillance that transforms how rice milling operations manage worker health and productivity. Lin et al. (2022) developed an automatic system using OpenPose that selects the appropriate ergonomic assessment method based on joint angles derived from video, reducing evaluation time for high-risk movement identification by approximately 90% compared to manual expert review. These capabilities allow TES to function as an early warning system: once the cumulative score approaches the critical threshold τ, the system flags the specific worker and workstation for intervention before throughput degradation begins. Fan et al. Fan et al. (2022) showed that structured light sensors paired with automated REBA assessment programs reduced assessment time by over 95% compared to expert measurements while maintaining consistent accuracy, demonstrating the operational viability of continuous monitoring in clinical settings with direct parallels to industrial deployment. Huang et al. Huang et al. (2020) validated a wearable inertial sensor system that achieved 88.3% classification accuracy for RULA and 91.7% for REBA when compared to expert raters, and their system visualized scores at each time point during task execution together with descriptive statistics including average score, duration, and risk distribution. This type of operator-specific risk profiling, adapted to a vision-based pipeline in rice mills, allows supervisors to identify which workers accumulate TES fastest and at which workstations, enabling targeted rest scheduling and personalized task assignment rather than uniform rotation policies.

2) Human-Machine Integration

Integrating TES-based feedback into the operational workflow of rice mills creates a closed-loop system where ergonomic data directly informs task design, workstation configuration, and labor allocation decisions. Lorenzini et al. Lorenzini et al. (2023) reviewed ergonomic human-robot collaboration frameworks and found that increasingly advanced control strategies have the potential to foster efficient coordination during hybrid tasks by meeting human counterparts' needs and limits, a principle that applies equally to human-machine systems in semi-mechanized rice milling where workers interact with dehuskers, polishers, and bagging equipment. Cardoso et al. Cardoso et al. (2021) documented that real-time ergonomic applications in collaborative workstations provide robots with the cognitive ability to communicate with operators and make adjustments during task execution, and this same logic extends to adaptive workflow design in rice mills where machine feed rates or conveyor speeds are adjusted based on the operator's accumulating TES value. Digiesi et al. (2018) proposed a mixed integer programming model for job rotation that minimizes ergonomic risk exposure while maintaining production targets, achieving optimal rotation schedules that jointly satisfy productivity and risk goals. Applying this approach with TES as the risk input allows rice mill managers to redistribute tasks among workers when any individual's cumulative score approaches the threshold, rather than waiting for complaints or visible fatigue. Quiroz-Flores et al. (2023) demonstrated that redesigning workstation methodologies based on RULA and REBA evaluations reduced risk levels by 50% to 66.7% in a plastics manufacturing plant, producing measurable savings in absenteeism costs.

3) Predictive Productivity Analytics

Modelling workers as dynamic biomechanical systems rather than static labour units fundamentally changes how rice mill operations forecast and manage productivity. Savin et al. (2021) provided direct evidence for this perspective by showing that kinematic adaptations during repetitive upper limb tasks appeared from 65% of total task completion time onward, with individual movement cycles deviating progressively from initial patterns in ways that standard ergonomic tools failed to capture. Brambilla et al. (2023) confirmed through a systematic review of 288 studies that biomechanical and physiological changes in fatigued muscles are detectable through instrumental assessments, and that multi-domain approaches combining kinematic, electromyographic, and temporal data offer the strongest predictive capacity for fatigue onset. Trost et al. (2022) reviewed production planning literature and found that models incorporating employee-related social aspects, including health and safety factors, into scheduling decisions achieved better balance between output targets and worker wellbeing, though most existing approaches consider only single aspects on single planning levels. TES addresses this gap by providing a unified, continuously updated metric that production planning systems ingest as a dynamic constraint. Menezes et al. (2022) documented in a metallurgical electrolysis unit that increased deformities in copper cathodes corresponded with increased on-time activities requiring awkward postures, establishing a direct empirical link between worker biomechanical state and product quality outcomes. Chatzis et al. (2022) proposed a variational deep learning architecture for automatic REBA estimation from RGB images that models human postures through a descriptive skeletal latent space, achieving state-of-the-art accuracy on benchmark datasets and demonstrating that posture-based risk prediction is computationally tractable at scale. In rice milling, where output quality depends on consistent manual handling during sorting, bagging, and equipment feeding, predictive analytics built on TES allow operations managers to anticipate productivity dips hours before they manifest, schedule preventive interventions, and maintain stable throughput across full production shifts.

E. Research Gaps and Future Directions

1) Validation Across Diverse Milling Environments

The TES framework and its associated vision-based pipeline require extensive validation across rice milling facilities that differ in scale, mechanization level, workflow configuration, and geographic context. Kee, (2022) demonstrated that RULA, REBA, and OWAS produce systematically different risk ratings depending on the task type and industry sector, with agreement rates between methods varying substantially across manufacturing, healthcare, forestry, and agriculture. Varghese et al. (2025) confirmed that the suitability of each ergonomic tool depends on the specific demands of the work activity, meaning that the weighting coefficients α, β, and γ in the TES formulation are likely task-dependent and environment-specific. Menezes et al. (2022) showed that even within a single metallurgical electrolysis unit, the criticality of postural exposure varied across different operational zones and activity types, reinforcing the need for site-specific calibration. Rice milling operations range from small-scale manual facilities where workers perform nearly all tasks by hand to large semi-automated plants where human labour concentrates at specific bottleneck stations such as bagging and quality sorting. The threshold parameter τ and scaling constant k in the TES-throughput model will differ across these settings. Future research must collect paired ergonomic and productivity data from multiple milling environments spanning different regions, production volumes, and workforce demographics to establish the generalizability of TES parameters and to determine whether a universal calibration protocol is feasible or whether facility-specific tuning remains necessary.

2) Integration with Wearable Sensors

Vision-based monitoring systems face inherent limitations in environments with occlusion, poor lighting, dust, and complex spatial layouts, all of which characterize typical rice milling facilities. Baklouti et al. (2024) demonstrated that IMU-based wearable systems detected a higher occurrence of postures warranting investigation compared to traditional RULA assessments, and their system achieved an intraclass correlation coefficient of 0.72 ± 0.23 for joint patterns across participants, indicating consistent measurement even in constrained industrial settings. Brambilla et al. (2023) found through a systematic review of 288 studies that instrumental assessments including electromyography and inertial measurement units are common in laboratory settings but underused in actual workplaces, where questionnaires and observational scales still dominate. Fusing wearable sensor data with vision-based pose estimation offers a path to more robust TES computation: cameras provide spatial context and whole-body posture information while wearables supply precise joint kinematics during occluded phases. Safari et al. (2025) confirmed that integrating AI with wearable devices enables real-time monitoring of workers' movements and postures, identifying hazards associated with musculoskeletal disorders with improved efficiency and accuracy compared to either modality alone. Future work should develop sensor fusion architectures that combine these complementary data streams to produce reliable TES estimates under the challenging environmental conditions found in rice mills.

3) Machine Learning Estimation of TES Parameters

The TES model contains parameters, specifically the weighting coefficients α, β, γ, the dynamic attenuation constant λ, the threshold τ, and the scaling constant k, that must be estimated from empirical data. Current ergonomic assessment tools rely on fixed scoring tables derived from expert consensus rather than data-driven optimization (Kee, 2022; Lorenzini et al. (2023). Paudel et al. (2022) showed that 3D pose estimation networks achieve over 90% accuracy in replicating OWAS, REBA, and RULA scores, establishing that machine learning models extract ergonomic features from video with high fidelity. Chatzis et al. Chatzis et al. (2022) proposed a variational deep learning architecture that estimates REBA scores through a descriptive skeletal latent space, achieving state-of-the-art accuracy on benchmark datasets and demonstrating that neural networks learn the nonlinear mapping from posture to risk score effectively. Cruciata et al. (2025) achieved F1-scores exceeding 0.99 for frame-level ergonomic classification using a lightweight Vision Transformer, confirming that deep learning models handle the multi-label, multi-region scoring required for TES computation. Lin et al. (2022) developed a decision tree that automatically selects the appropriate ergonomic assessment method based on joint angles derived from OpenPose, reducing evaluation time by approximately 90%. These advances suggest that end-to-end learning frameworks could estimate TES parameters directly from paired video and productivity data, bypassing manual calibration entirely. Wang et al. (2023) applied fuzzy logic to REBA scoring to capture continuous transition features, achieving a correlation coefficient of 0.817 with standard REBA, pointing toward hybrid approaches that combine domain knowledge with learned parameters. Future research should explore supervised and reinforcement learning methods for jointly optimizing all TES parameters against throughput loss data collected from rice milling operations.

4) Real-Time Deployment Challenges

Deploying TES-based monitoring in operational rice mills introduces practical challenges related to computational cost, environmental interference, worker acceptance, and system reliability. Cruciata et al. (2025) designed their lightweight Vision Transformer specifically for real-time inference on edge devices, recognizing that industrial environments often lack the computational infrastructure for cloud-based processing. Fan et al. (2022) reported that their structured light sensor system reduced ergonomic assessment time by over 95% compared to expert measurements, but their deployment was in a controlled clinical setting with stable lighting and minimal occlusion, conditions that rice mills do not provide. Lorenzini et al. (2023) identified that real-time ergonomic applications in collaborative workstations remain in early stages, with most systems validated only in laboratory or simulated environments rather than in active production facilities. Dust, vibration, variable lighting, and the movement of large equipment create signal degradation for both cameras and wearable sensors in milling environments. Cardoso et al. (2021) noted that real-time ergonomic applications require robots and systems with the cognitive ability to communicate with operators and adjust during task execution, raising questions about how workers respond to continuous monitoring and automated feedback. Privacy concerns, data security, and worker trust represent additional barriers that technical solutions alone do not address (Safari et al., 2025). Future research must conduct longitudinal field trials in operating rice mills to quantify system robustness under real conditions, measure worker compliance and behavioral responses to TES-based alerts and develop degradation-tolerant algorithms that maintain acceptable accuracy when sensor inputs are noisy or intermittent.

IV. Conclusion

Ergonomic risk predicts operational inefficiency only when it is treated as a cumulative, time-resolved exposure rather than a single postural snapshot. Across the manuscript, RULA, REBA, and OWAS provide useful postural screening logic, yet each remains limited by static or discretized scoring and cannot represent motion adaptation, exposure accumulation, or the threshold behavior through which fatigue translates into throughput loss. The proposed Temporal Ergodic Score addresses this gap by integrating frame-wise ergonomic scores over time and attenuating risk under active motion through angular velocity. In this form, ergonomic assessment moves from descriptive posture classification to a direct operational indicator. Within rice milling, this gives a clearer basis for identifying when repetitive lifting, bending, and carrying begin to erode task speed, coordination, accuracy, and output. The study therefore places ergonomics within production analysis itself, where continuous vision-based monitoring supports earlier intervention, better task rotation decisions, and more reliable protection of throughput across the work shift.

References

Agostinelli, T., Generosi, A., Ceccacci, S., & Mengoni, M. (2024). Validation of computer vision-based ergonomic risk assessment tools for real manufacturing environments. Scientific Reports, 14(1). -https://doi.org/10.1038/s41598-024-79373-4

Aswalekar, U. and Tungikar, V. (2018). Assessment Of Ergonomic Environment and Risk Factors for Musculoskeletal Disorders Among Welders in Micro, Small, and Medium-Sized Enterprises. IEJ, 10(5). https://doi.org/10.26488/iej.10.5.34

Babangida, A., Caraballo-Arias, Y., Decataldo, F., & Violante, F. (2025). Advancing Occupational Medicine through Wearable Technology: A Review of Sensor Systems for Biomechanical Risk Assessment and Work-Related Musculoskeletal Disorder Prevention. Acs Sensors, 10(8), 5410-5432. https://doi.org/-10.1021/acssensors.5c01578

Baklouti, S., Chaker, A., Rezgui, T., Sahbani, A., Bennour, S., & Laribi, M. (2024). A Novel IMU-Based System for Work-Related Musculoskeletal Disorders Risk Assessment. Sensors, 24(11), 3419. https://doi.-org/10.3390/s24113419

Banga, H., Kumar, R., & Kalra, P. (2022). Ergonomics evaluation of lawn mower operator's working posture using JACK software and Kinect interface. Work, 72(2), 497-510. https://doi.org/10.3233/wor-210713

Benos, L., Tsaopoulos, D., & Bochtis, D. (2020). A Review on Ergonomics in Agriculture. Part I: Manual Operations. Applied Sciences, 10(6), 1905. https://-doi.org/10.3390/app10061905

Brambilla, C., Nicora, M., Storm, F., Reni, G., Malosio, M., & Scano, A. (2023). Biomechanical Assessments of the Upper Limb for Determining Fatigue, Strain and Effort from the Laboratory to the Industrial Working Place: A Systematic Review. Bioengineering, 10(4), 445. https://doi.org/10.3390/bioengineering10040445

Brinkmann, A., Fifelski, C., Kowalski, C., Lau, S., Meyer, O., Diekmann, R., … & Hein, A. (2022). Providing physical relief for nurses by collaborative robotics. Scientific Reports, 12(1). https://doi.org/10.1038/-s41598-022-12632-4

Brito, M., Ramos, A., Carneiro, ́., & Gonçalves, M. (2018). Integration of lean manufacturing and ergonomics in a metallurgical industry. International Journal of Occupational and Environmental Safety, 2(2), 21-31. https://doi.org/10.24840/2184-0954_002.002_0003

Can, G. (2018). A Mathematical Model for Determining Job Rotation Strategy Considering Mental and Physical Fatique. Ergonomics International Journal, 2(5), 1-9. https://doi.org/10.23880/eoij-16000181

Can, G. (2018). A Mathematical Model for Determining Job Rotation Strategy Considering Mental and Physical Fatique. Ergonomics International Journal, 2(5), 1-9. https://doi.org/10.23880/eoij-16000181

Can, G. (2018). A Mathematical Model for Determining Job Rotation Strategy Considering Mental and Physical Fatique. Ergonomics International Journal, 2(5), 1-9. https://doi.org/10.23880/eoij-16000181

Cardoso, A., Colim, A., Bicho, E., Braga, A., Menozzi, M., & Arezes, P. (2021). Ergonomics and Human Factors as a Requirement to Implement Safer Collaborative Robotic Workstations: A Literature Review. Safety, 7(4), 71. https://doi.org/10.3390/safety7040071

Chatzis, T., Konstantinidis, D., & Dimitropoulos, K. (2022). Automatic Ergonomic Risk Assessment Using a Variational Deep Network Architecture. Sensors, 22(16), 6051. https://doi.org/10.3390/s22166051

Collins, R., Rensburg, D., & Patricios, J. (2011). Common work-related musculoskeletal strains and injuries. South African Family Practice, 53(3), 240-246. https://doi.org/10.1080/20786204.2011.10874091

Conforti, I., Mileti, I., Prete, Z., & Palermo, E. (2020). Measuring Biomechanical Risk in Lifting Load Tasks Through Wearable System and Machine-Learning Approach. Sensors, 20(6), 1557. https://doi.org/10.33-90/s20061557

Cruciata, L., Contino, S., Ciccarelli, M., Pirrone, R., Mostarda, L., Papetti, A., & Piangerelli, M. (2025). Lightweight vision transformer for frame-level ergonomic posture classification in industrial workflows. *Sensors*, *25*(15), 4750. https://doi.org/10.-3390/s25154750

Digiesi, S., Facchini, F., Mossa, G., & Mummolo, G. (2018). Minimizing and balancing the ergonomic risk of assembly-line workers through job rotation: A MINLP Model. *International Journal of Industrial Engineering and Management*, *9*(3), 129, 129-138. https://doi.org/10.24867/ijiem-2018-3-129

Fan, L. J., Liu, S., Jin, T., Gan, J. G., Wang, F. Y., Wang, H. T., & Lin, T. (2022). Ergonomic risk factors and work-related musculoskeletal disorders in clinical physiotherapy. *Frontiers in public health*, *10*, 1083-609. https://doi.org/10.3389/fpubh.2022.1083609

Yovi, E. Y., & Wilantara, B. (2023). Does motor manual pine oleoresin tapping bring work-related musculoskeletal disorders risk to the tappers?(RoM, REBA, RULA, and OWAS based postural analysis). *Jurnal Sylva Lestari*, *11*(1), 123-135.

Fathimahhayati, L., Pawitra, T., Tambunan, W., & Hartono, M. (2021). Working posture analysis on oyster mushroom farmers using OWAS method in Lempake, Samarinda, East Kalimantan. Jurnal Ilmiah Pertanian, 18(1), 1-11. https://doi.org/10.31849/jip.v18i1.7197

Gómez-Galán, M., González-Parra, J., Pérez-Alonso, J., Golasi, I., & Ferre, Á. (2019). Forced Postures in Courgette Greenhouse Workers. Agronomy, 9(5), 253. https://doi.org/10.3390/agronomy9050253

Gómez-Galán, M., Pérez-Alonso, J., Ferre, Á., & López-Martínez, J. (2017). Musculoskeletal disorders: OWAS review. Industrial Health, 55(4), 314-337. https://doi.org/10.2486/indhealth.2016-0191

Gu, S., Zhang, T., Wang, H., & Wang, Q. (2025). A Quantifiable Comprehensive Evaluation Method Combining Optical Motion Capture and Simulation-Assessing the Layout Design of Special Vehicle Cabins. Sensors, 25(16), 5053. https://doi.org/10.33-90/s25165053

Hanson, L., Keyvani, A., Lämkull, D., Örtengren, R., Högberg, D., Rhén, I., … & Forsman, M. (2018). Ergonomic risk assessment in DHM tools employing motion data - exposure calculation and comparison to epidemiological reference data. International Journal of Human Factors Modeling and Simulation, 6(1), 31. https://doi.org/10.1504/ijhfms.2018.10012500

Hasheminejad, N., Amirmahani, M., & Tahernejad, S. (2023). Biomechanical evaluation of midwifery tasks and its relationship with the prevalence of musculoskeletal disorders. *Heliyon*, *9*(9). https://-doi.org/10.1016/j.heliyon.2023.e19442

Liu, Q., Han, Z., Liu, F., & Yang, J. (2024). Comfort evaluation of carrier-based aircraft missile handling operation based on fuzzy analytic hierarchy process. *Advances in Mechanical Engineering*, *16*(9), 16878132241286410.

Hay, A., Sayed, W., & Saleh, M. (2019). Correlation Between Musculoskeletal Disorders and Work Related Postures in Physical Therapists. South Valley University International Journal of Physical Therapy and Sciences, 1(1), 20-29. https://doi.org/10.21608/-svupts.2019.231026

Hida, T., Okada, T., & Matsumoto, T. (2022). Work postural ergonomic assessment using two-dimensional joint coordinates. Journal of Advanced Mechanical Design Systems and Manufacturing, 16(5), JAMDSM0055-JAMDSM0055. https://doi.org/10.1299/jamdsm.-2022jamdsm0055

Hossain, M., Azam, S., Karim, A., Montaha, S., Quadir, R., Boer, F., … & Altaf-Ul-Amin, M. (2023). Ergonomic Risk Prediction for Awkward Postures From 3D Keypoints Using Deep Learning. IEEE Access, 11, 114497-114508. https://doi.org/10.1109/access.-2023.3324659

Huang, C., Kim, W., Zhang, Y., & Xiong, S. (2020). Development and Validation of a Wearable Inertial Sensors-Based Automated System for Assessing Work-Related Musculoskeletal Disorders in the Workspace. International Journal of Environmental Research and Public Health, 17(17), 6050. https://-doi.org/10.3390/ijerph17176050

Hussain, A., Case, K., Marshall, R., & Summerskill, S. (2016). Using Ergonomic Risk Assessment Methods for Designing Inclusive Work Practices: A Case Study. Human Factors and Ergonomics in Manufacturing & Service Industries, 26(3), 337-355. https://doi.org/10.1002/hfm.20650

Jafarvand, M., Keshmiri, B., & Varmazyar, S. (2017). Determination of the Risk Level of Work Posture by REBA and RULA Methods among Workers of Assembly Lines of a Cosmetics Manufacturing Factory. https://doi.org/10.29252/jhehp.3.1.2

Kahya, E. and ŞAHİN, B. (2019). A new model proposal for ergonomic assembly line balancing. Mühendislik Bilimleri Ve Tasarım Dergisi, 7(4), 767-778. https://-doi.org/10.21923/jesd.468028

Kajaks, T., Ziebart, C., Galea, V., Vrkljan, B., & MacDermid, J. (2023). Posture Evaluation of Firefighters During Simulated Fire Suppression Tasks. Workplace Health & Safety, 71(12), 606-616. https://doi.org/10.1177/-21650799231214275

Kee, D. (2022). Systematic Comparison of OWAS, RULA, and REBA Based on a Literature Review. International Journal of Environmental Research and Public Health, 19(1), 595. https://doi.org/10.3390/-ijerph19010595

Kibria, M. (2023). Ergonomic Analysis of Working Postures at a Construction Site Using Rula and Reba Method. Journal of Engineering Science, 14(1), 43-52. https://doi.org/10.3329/jes.v14i1.67634

Kress, G. (1994). Workplace Ergonomics: An Approach to Health, Safety, and Productivity.. https://doi.org/-10.1115/cec1994-4003

Kusmindari, C., Indriani, P., Nu'man, A., Muthmainah, S., & Erina, I. (2022). Analysis of the workload of Dock 16 Ilir workers using the Rapid Upper Limb Assessment, the Ovako Working Analysis System, and the Nordic Body Map Methods: A quantitative case study. F1000Research, 11, 788. https://doi.org/10.12688/-f1000research.122131.1

Kwon, Y. J., Kim, D. H., Son, B. C., Choi, K. H., Kwak, S., & Kim, T. (2022). A work-related musculoskeletal disorders (WMSDs) risk-assessment system using a single-view pose estimation model. *International journal of environmental research and public health*, *19*(16), 9803. https://doi.org/10.3390/ijerph-19169803

Landekić, M., Katuša, S., Mijoč, D., & Šporčić, M. (2019). Assessment and Comparison of Machine Operators' Working Posture in Forest Thinning. South-East European Forestry, 10(1), 29-37. https://doi.org/10.-15177/seefor.19-02

Lazăr, A., Repanovici, A., Baritz, M., Scutariu, M., Tătaru, A., & Pantea, I. (2024). Postural Risks in Dental Practice: An Assessment of Musculoskeletal Health. Sensors, 24(19), 6240. https://doi.org/10.3390/-s24196240

Leggieri, S., Fanti, V., Caldwell, D., & Natali, C. (2023). Online Ergonomic Evaluation in Realistic Manual Material Handling Task: Proof of Concept. Bioengineering, 11(1), 14. https://doi.org/10.3390/-bioengineering11010014

Li, X., Han, S., Gül, M., & Al-Hussein, M. (2016). 3D Motion-based Ergonomic and Body Posture Analysis in Construction. Modular and Offsite Construction (Moc) Summit Proceedings. https://doi.org/10.-29173/mocs27

Li, Z., Zhang, R., Lee, C., & Lee, Y. (2020). An Evaluation of Posture Recognition Based on Intelligent Rapid Entire Body Assessment System for Determining Musculoskeletal Disorders. Sensors, 20(16), 4414. https://doi.org/10.3390/s20164414

Lin, P., Chen, Y., Wei-Shin, C., & Lee, Y. (2022). Automatic real-time occupational posture evaluation and select corresponding ergonomic assessments. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-05812-9

Liu, Q., Han, Z., Liu, F., & Yang, J. (2024). Comfort evaluation of carrier-based aircraft missile handling operation based on fuzzy analytic hierarchy process. Advances in Mechanical Engineering, 16(9). https://doi.org/10.1177/16878132241286410

Lorenzini, M., Lagomarsino, M., Fortini, L., Gholami, S., & Ajoudani, A. (2023). Ergonomic human-robot collaboration in industry: A review. Frontiers in Robotics and AI, 9. https://doi.org/10.3389/frobt.2022.813907

Medic-Pericevic, S., Mikov, I., Spanovic, M., Maric, N., Zvekic-Svorcan, J., & Krasnik, R. (2024). De Quervain's tenosynovitis as an occupational disease in an agricultural worker: A case report. *Work*, *79*(2), 999-1005. https://doi.org/10.3233/wor-230135

Menezes, M., Haddad, A., & Nascimento, M. (2022). Practical Application of Ergonomic Methodology Identifying Critical Activities in a Metallurgical Electrolysis Unit. IEEE Access, 10, 109132-109152. https://doi.org/10.1109/access.2022.3213045

Mgbemena, C., Tiwari, A., Xu, Y., Prabhu, V., & Hutabarat, W. (2020). Ergonomic evaluation on the manufacturing shop floor: A review of hardware and software technologies. Cirp Journal of Manufacturing Science and Technology, 30, 68-78. https://doi.org/10.1016/j.cirpj.2020.04.003

Mohamed, N. M. Z. N., & Rashid, M. F. F. A. (2022). Analysis of measurement and calculation of MSD complaint of chassis assembly workers using OWAS, RULA and REBA method. *International Journal of Automotive and Mechanical Engineering*, *19*(2), 9681-9692. https://doi.org/10.15282/ijame.19.2.2022.05.0747

Paudel, P., Kwon, Y., Kim, D., & Choi, K. (2022). Industrial Ergonomics Risk Analysis Based on 3D-Human Pose Estimation. Electronics, 11(20), 3403. https://doi.org/10.3390/electronics11203403

Petruse, R. E., & Vlad, S. M. (2023). Optimizing Manual Assembly Operations: Ergonomics Analysis and Human-Robot Collaboration. *Acta Universitatis Cibiniensis. Technical Series*, *75*(1), 1-13. https://doi.org/10.2478/aucts-2023-0001

Pinzke, S. and Lavesson, L. (2018). Ergonomic conditions in manual harvesting in Swedish outdoor cultivation. Annals of Agricultural and Environmental Medicine, 25(3), 481-487. https://doi.org/10.26444/aaem/93334

Pratiwi, I., Fitriadi, R., & Sufa, M. (2019). Evaluation of Work Posture in Sohun Noodles Workers using OWAS and WERA Method. International Journal of Innovative Technology and Exploring Engineering, 8(11), 1788-1793. https://doi.org/10.35940/ijitee.k1767.0981119

Quiroz-Flores, J., Abásolo-Núñez, B., Suárez-Miñano, D., & Nallusamy, S. (2023). Minimization of Personnel Absenteeism with the Application of Proposed Ergonomic Model in a Plastics Manufacturing Industry. Applied Sciences, 13(13), 7858. https://doi.org/10.3390/app13137858

Rout, B., Dash, R., & Dhupal, D. (2019). Optimal Posture Prediction in Brick Stacking Operation to Reduce Ergonomic Risk Factors. International Journal of Recent Technology and Engineering, 8(3), 1835-1841. https://doi.org/10.35940/ijrte.c4634.098319

Rybnikár, F., Kačerová, I., Hořejší, P., & Simon, M. (2022). Ergonomics Evaluation Using Motion-Capture Technology: Literature Review. Applied Sciences, 13(1), 162. https://doi.org/10.3390/app13010162

Safari, M., Naserbakht, A., Kouhi, A., & Varmazyar, S. (2025). Artificial intelligence and emerging technologies in assessing ergonomic risk factors in the workplace: A systematic review. Work: A Journal of Prevention Assessment & Rehabilitation, 82(3), 727-739. https://doi.org/10.1177/10519815251349793

Savin, J., Gaudez, C., Gilles, M., Padois, V., & Bidaud, P. (2021). Evidence of movement variability patterns during a repetitive pointing task until exhaustion. Applied Ergonomics, 96, 103464. https://doi.org/10.1016/j.apergo.2021.103464

Singh, L. (2018). Prevalence of MSDs among Nurses: A Study in Indian Health Care Industry. Ergonomics International Journal, 2(4). https://doi.org/10.23880/eoij-16000149

Tee, K. S., Low, E., Saim, H., Zakaria, W. N. W., Khialdin, S. B. M., Isa, H., ... & Soon, C. F. (2017, September). A study on the ergonomic assessment in the workplace. In *AIP conference proceedings* (Vol. 1883, No. 1, p. 020034). AIP Publishing LLC. https://doi.org/10.1063/1.5002052

Trost, M., Claus, T., & Herrmann, F. (2022). Social Sustainability in Production Planning: A Systematic Literature Review. Sustainability, 14(13), 8198. https://doi.org/10.3390/su14138198

Varghese, A., Panicker, V., & George, J. (2025). Posture Assessment of Rubber Tappers: A Comparative Analysis of OWAS, REBA, RULA, and PERA Methods, 116(3), 15875. https://doi.org/10.23749/mdl.v116i3.15875

Vilas, D., Longo, F., & Monteil, N. (2012). A general framework for the manufacturing workstation design optimization: a combined ergonomic and operational approach. Simulation, 89(3), 306-329. https://doi.org/10.1177/0037549712462862

Wang, Z., Wang, W., Chen, J., Zhang, X., & Miao, Z. (2023). Posture Risk Assessment and Workload Estimation for Material Handling by Computer Vision. International Journal of Intelligent Systems, 2023(1). https://doi.org/10.1155/2023/2085251

Winiarski, S., Molek-Winiarska, D., Chomątowska, B., Sipko, T., & Dyvak, M. (2021). Added value of motion capture technology for occupational health and safety innovations. Human Technology, 17(3). https://doi.org/10.14254/1795-6889.2021.17-3.4

Yamamoto, S. (1997). A New Trend in the Study of Low Back Pain in Workplaces. Industrial Health, 35(2), 173-185. https://doi.org/10.2486/indhealth.35.173

Yovi, E. and Wilantara, B. (2023). Does Motor Manual Pine Oleoresin Tapping Bring Work-Related Musculoskeletal Disorders Risk to the Tappers? (RoM, REBA, RULA, AND OWAS Based Postural Analysis). Jurnal Sylva Lestari, 11(1), 123-135. https://doi.org/10.23960/jsl.v11i1.664

Zhang, R. and Huang, M. (2024). A Quick Capture Evaluation System for the Automatic Assessment of Work-Related Musculoskeletal Disorders for Sanitation Workers. Applied Sciences, 14(4), 1542. https://doi.org/10.3390/app14041542