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Digital ergonomics and AI-based evaluation in agricultural work systems

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Abstract

Agriculture remains one of the most physically demanding occupations, with workers regularly exposed to repetitive movements, awkward postures, manual material handling, vibration, heat stress, and other environmental hazards that results in a high prevalence of work-related musculoskeletal disorders (WMSDs). Conventional ergonomic assessment methods, such as Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and Ovako Working Posture Assessment System (OWAS), are mainly based on manual observation and are often limited by subjectivity, time consumption, and poor applicability under dynamic field conditions. Recent advances in Agriculture 4.0 have accelerated the integration of digital technologies, enabling objective, continuous, and predictive ergonomic evaluation. This review synthesizes recent developments in digital ergonomics and artificial intelligence (AI)-based ergonomic assessment for agricultural work systems. It examines the application of wearable sensors, Internet of Things (IoT) platforms, computer vision, motion capture systems, Digital Human Modeling (DHM), digital twins, robotics, and machine learning techniques for real-time monitoring of worker posture, physiological responses, and environmental exposures. The review further discusses AI-driven approaches, including machine learning, deep learning, and decision-support systems, for automated posture recognition, ergonomic risk classification, and early prediction of WMSDs. Practical applications in harvesting, planting, weeding, manual material handling, and tractor operation are highlighted, demonstrating the potential of digital technologies to enhance worker safety, improve ergonomic design, and increase operational efficiency. Current challenges, such as technical limitations, data availability, worker acceptance, economic constraints, and the lack of long-term field validation, are also critically discussed. Future research should focus on field validation with robustness, integration of multiple sensors, lightweight AI models, human-centered system design, and intelligent decision-support frameworks to enable the transition toward predictive, data-driven occupational health management in smart agriculture.

Keywords: Agricultural ergonomics, digital ergonomics, artificial intelligence, agriculture 4.0, work-related musculoskeletal disorders, wearable sensors, computer vision, machine learning, posture assessment, occupational health

1. Introduction

Agriculture continues to be an important part of the global economy, providing food, fiber, and raw materials while supporting the livelihoods of millions of people. Even with great progress in agricultural mechanization, farming continues to be one of the most physically demanding and hazardous occupations. Agricultural workers are routinely exposed to repetitive movements, manual material handling, prolonged bending, kneeling, twisting, and unfavorable environmental conditions such as extreme temperatures and solar radiation. These occupational demands are a major factor in the occurrence of work-related musculoskeletal disorders (WMSDs), which remain among the most common non-fatal occupational health problems affecting agricultural workers worldwide (Benos *et al.*, 2020; Apicella & Tarabella, 2025) ^[5, 8]. Conventional ergonomic assessment methods, including Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and the Ovako Working Posture Assessment System (OWAS), have long served as standard tools for identifying postural risks. However, these approaches rely primarily on manual observation, making them labor-intensive, subjective, and difficult to apply consistently under dynamic field conditions.

Furthermore, dependence on observer judgment and worker self-reporting often results in underreporting of ergonomic hazards and limits the early identification of injury risks, thereby reducing the effectiveness of preventive interventions in real agricultural environments (Singh *et al.*, 2024; Yousefi *et al.*, 2026) ^[50, 56]. The emergence of Agriculture 4.0 has accelerated the adoption of digital technologies that address many of these limitations. Digital ergonomics combines wearable sensing technologies, computer vision, artificial intelligence (AI), Internet of Things (IoT) platforms, and Digital Human Modeling (DHM) to enable continuous monitoring of workers, automated posture recognition, and predictive ergonomic risk assessment. Wearable devices such as inertial measurement units (IMUs), biometric sensors, and smart glasses provide objective biomechanical and physiological measurements, while AI-based computer vision systems automate posture analysis using skeletal tracking and deep learning algorithms. Simultaneously, Digital Human Modeling and Computer-Aided Design (CAD) facilitate virtual simulation of human-machine interactions during equipment design, allowing ergonomic deficiencies to be identified before physical prototypes are developed (Apicella & Tarabella, 2025; Patel *et al.*, 2016) ^[5, 38]. Against this background, this review synthesizes recent advances in digital ergonomics and AI-based ergonomic evaluation within agricultural work systems. Emphasis is placed on digital sensing technologies, wearable devices, computer vision, machine learning, digital twins, and human-centered design approaches that support continuous ergonomic monitoring across both manual agricultural activities, such as

harvesting and pruning, and mechanized operations including tractor driving and machinery operations. The review further examines emerging applications, current challenges, and future research directions that support the transition from conventional reactive safety management toward predictive, data-driven occupational health systems.

2. Digital Ergonomics

Digital ergonomics, frequently referred to as “cybergonomics”, represents the integration of classical ergonomic principles with emerging technologies associated with Industry 4.0 and Agriculture 4.0, including artificial intelligence, robotics, IoT, wearable sensing, and digital simulation. Rather than relying solely on observational assessments performed after ergonomic problems occur, digital ergonomics continuously acquires, transmits, and analyzes physiological, biomechanical, and environmental data to support real-time monitoring and predictive decision-making. In this framework, agricultural workers become active components of smart farming ecosystems through continuous interaction with digital technologies (Apicella & Tarabella, 2025; Benos *et al.*, 2020) ^[5, 8]. A central component of digital ergonomics is Ergonomic Posture Risk Assessment (EPRA), which aims to identify potentially hazardous working postures before musculoskeletal injuries develop. Compared with traditional observation-based EPRA methods, computer vision-based approaches provide automated posture evaluation by continuously extracting biomechanical information from workers during actual field operations, thereby reducing observer bias and improving assessment consistency (Figure 1).

Observation-based EPRA	CV-based EPRA
 Relies on manual observation by experts or trained observers.	 Uses cameras to automatically collect workers' motion and posture data.
 Time-consuming and limited by the observer's ability to record.	 Highly efficient, with the capability to continuously and in real-time capture and analyze vast volumes of data.
 Limit the scalability and integration capabilities with other data analysis systems or management tools.	 Integrate with advanced technologies such as AI, machine learning, and big data platforms to enable higher-level data analysis and management.
 Involve relatively low initial costs but may necessitate a greater investment of human resources for data analysis.	 Involve potentially high initial investments, but save on human resource costs and enhance assessment efficiency in the long run.

Fig 1: Observation-based EPRA vs CV-based EPRA

The scope of digital ergonomics extends across both manual and mechanized agricultural activities. During manual operations such as harvesting, pruning, and material handling, digital systems quantify joint movements, posture, muscle activity, and physiological workload. In mechanized operations, including tractor driving and machinery operation, these systems additionally monitor exposure to whole-body vibration, environmental stressors, and operator behavior. Consequently, digital ergonomics encompasses three complementary domains of assessment:

- **Biomechanical monitoring**, including joint angles, body movements, posture, and movement dynamics;
- **Physiological monitoring**, including heart rate, muscle activation, fatigue, thermal stress, and cardiovascular responses; and
- **Environmental monitoring**, including vibration exposure, climatic conditions, and hazardous workplace environments.

By integrating these complementary sources of information,

digital ergonomics enables a transition from retrospective injury evaluation toward proactive identification of ergonomic risks, allowing preventive interventions before occupational injuries occur.

2.1 Digital Tools in Ergonomic Assessment

Recent advances in digital technologies have fundamentally transformed ergonomic assessment from subjective observational methods into objective, data-driven monitoring systems capable of continuous evaluation. Wearable sensing technologies constitute one of the most widely adopted approaches for measuring workers' biomechanical and physiological responses during agricultural activities. Inertial Measurement Units (IMUs), surface electromyography (sEMG), accelerometers, and gyroscopes provide quantitative measurements of joint kinematics, body orientation, movement dynamics, and muscular activation, thereby enabling detailed assessment of physical workload (Kapse *et al.*, 2024; Hilmi *et al.*, 2024; Vitale *et al.*, 2024) [27, 30, 53].

Surface electromyography is particularly valuable for evaluating muscular effort during agricultural operations. Sensors positioned on muscles including the brachioradialis (BR), extensor digitorum (ED), flexor carpi radialis (FCR), and middle deltoid (MD) provide continuous measurements of muscle activation patterns associated with repetitive work tasks (Fig. 2) (Chouriya, 2025) [15]. Complementary physiological monitoring devices, such as Polar sensors, record heart rate and heart rate variability, enabling objective assessment of cardiovascular workload, fatigue, and worker stress responses throughout task performance (Fig. 3) (Chouriya, 2025) [15]. Computer vision and artificial intelligence have further expanded the capabilities of ergonomic assessment by automating conventional observational methods. Deep learning algorithms extract skeletal key points from RGB cameras or depth sensors such as Kinect V2, enabling automatic calculation of ergonomic indices including RULA and REBA without direct human observation (Singh *et al.*, 2024; Yang *et al.*, 2024; Yousefi *et al.*, 2026; Vitale *et al.*, 2024) [50, 53, 55, 56].

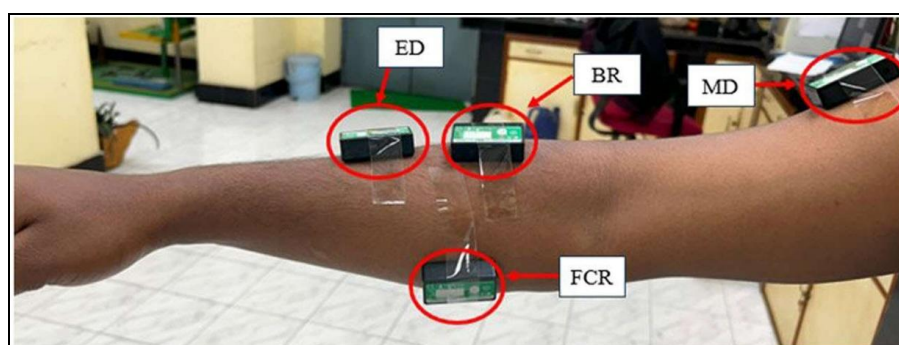


Fig 2: Placement of EMG sensors on selected muscles. BR, brachioradialis; ED, extensor digitorum; EMG, electromyography; FCR, flexor carpi radialis; MD, middle deltoid

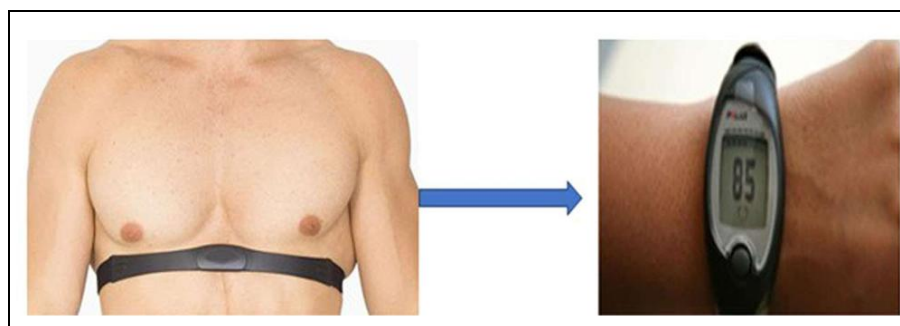


Fig 3: Polar sensor

In parallel, Digital Human Modeling (DHM), Digital Twins, and Virtual Reality (VR) technologies enable engineers to simulate human-machine interactions within virtual environments before physical equipment is manufactured. These technologies facilitate ergonomic evaluation of reachability, visibility, operator comfort, and workstation layout while supporting immersive training under risk-free conditions. When combined with advanced machine learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, these digital tools support predictive ergonomic management capable of identifying musculoskeletal risks before injuries occur (Apicella & Tarabella, 2025; Safari *et al.*, 2025; Kapse *et al.*, 2024; Singh *et al.*, 2024) [5, 30, 46, 50].

3. Role of Artificial Intelligence in Ergonomic Evaluation

Artificial Intelligence (AI) has become a core enabling technology within digital ergonomics by transforming

conventional ergonomic assessment from a reactive, observation-based process into a predictive, data-driven system. By processing large volumes of physiological, biomechanical, and visual data collected through wearable sensors and computer vision systems, AI supports continuous monitoring of workers, automated posture recognition, and early identification of ergonomic risks. Within Agriculture 4.0, AI extends digitalization to the human component of farming systems, integrating workers into intelligent production environments where occupational health can be continuously assessed and optimized (Apicella & Tarabella, 2025; Donisi *et al.*, 2022) [5, 19]. Rather than simply documenting existing hazards, AI-based ergonomic systems identify hidden movement patterns and workload trends that facilitate proactive interventions before work-related musculoskeletal disorders (WMSDs) develop (Naranjo *et al.*, 2025; Yang *et al.*, 2024) [37, 55].

3.1 Machine Learning for Posture Analysis

Machine learning (ML) forms the computational foundation of modern AI-based ergonomic evaluation by automating posture classification and ergonomic risk assessment. Traditional observational techniques require trained assessors to evaluate worker postures manually, making the process labor-intensive and susceptible to subjective variation. Machine learning algorithms overcome these limitations by learning relationships between biomechanical features and ergonomic risk categories from sensor and image datasets, enabling rapid and objective posture evaluation (Kapse *et al.*, 2024; Yang *et al.*, 2024) [30, 55].

Several conventional machine learning algorithms have been successfully applied for ergonomic posture classification, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forest (RF), and K-Nearest Neighbors (KNN). These algorithms classify worker postures into predefined ergonomic risk levels using features extracted from images, wearable sensors, or motion capture systems. By evaluating biomechanical parameters such as joint angles and body orientation, these models distinguish safe postures from those associated with elevated musculoskeletal risk.

The increasing availability of large visual datasets has accelerated the adoption of deep learning approaches that eliminate the need for manual feature engineering. Lightweight pose estimation models such as MoveNet automatically detect anatomical key points and classify trunk postures into categories including neutral posture and forward bending. Applications in agricultural environments, particularly nursery operations, have demonstrated posture classification accuracies approaching

87.8%, highlighting the potential of deep learning for reliable ergonomic monitoring under practical working conditions (Kapse *et al.*, 2024) [30].

Beyond static posture recognition, temporal machine learning models have expanded ergonomic assessment to include dynamic movement analysis. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, analyze sequential motion and wearable sensor data to recognize repetitive agricultural activities such as manual pruning and crate transportation. By incorporating temporal information, these models capture cumulative movement patterns and repetitive workload characteristics that cannot be identified through isolated posture observations, thereby enabling predictive assessment of ergonomic risks throughout the working day (Apicella & Tarabella, 2025) [5].

The general architecture of a computer vision- and machine learning-based Ergonomic Posture Risk Assessment (EPRA) system framework consists of three sequential stages: data preparation, pose estimation, and ergonomic risk assessment (Fig 4). Visual information acquired through RGB or depth cameras is first preprocessed before AI algorithms identify anatomical key points and generate skeletal representations of workers. The extracted biomechanical information is subsequently analyzed using standardized ergonomic assessment methods, including RULA and REBA, to estimate posture-related risk levels. Through continuous operation, this integrated framework provides objective, automated, and real-time ergonomic monitoring capable of identifying musculoskeletal risks before injury occurs.

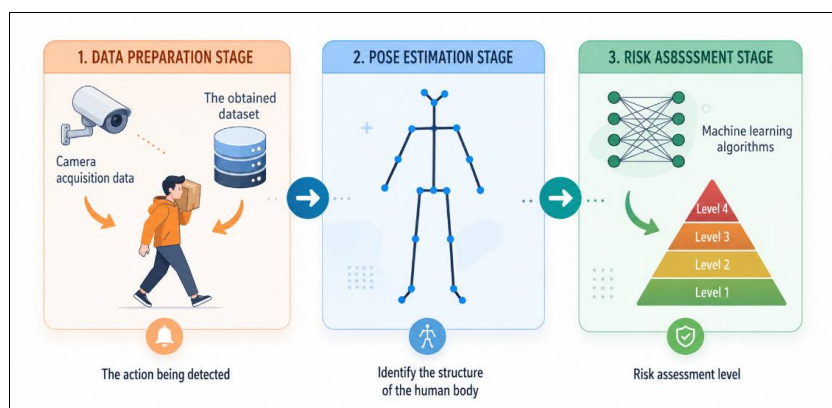


Fig 4: Three stages of Ergonomic Posture Risk Assessment (EPRA) system integrated with CV and ML

3.2 Computer Vision for Real-Time Ergonomic Monitoring

Computer Vision (CV) has emerged as one of the most promising technologies for real-time ergonomic assessment because it enables continuous, non-contact monitoring of workers without interfering with normal agricultural activities. Unlike wearable sensor systems, which require body-mounted devices, computer vision estimates body posture directly from video sequences, thereby reducing worker discomfort while supporting unobtrusive monitoring during routine field operations (Yang *et al.*, 2024; MassirisFernández *et al.*, 2020) [34, 55]. Modern pose estimation frameworks such as OpenPose and BlazePose automatically extract two-dimensional and three-dimensional skeletal information from image sequences by identifying anatomical landmarks and calculating joint angles. These digital skeletal models enable objective detection of awkward postures, unstable body configurations, and potentially hazardous movements that are associated with elevated ergonomic risk (Yang *et al.*, 2024; MassirisFernández *et al.*, 2020) [34, 55]. An important advantage of computer vision over

wearable technologies is its capability to monitor multiple workers simultaneously. AI-based image analysis systems perform unsupervised posture assessment across several individuals within the same working environment while maintaining continuous observation under varying illumination conditions and partial visual occlusions. Such capability is particularly valuable for large-scale agricultural operations where simultaneous monitoring of multiple workers is required (Yang *et al.*, 2024; MassirisFernández *et al.*, 2020) [34, 55].

Computer vision has also been incorporated into mechanized agricultural operations to evaluate human-machine interactions. Combined with motion capture technologies, these systems analyze the influence of tractor dashboard configurations, control locations, and display positioning on operator posture and muscular activity. Such analyses provide valuable information for optimizing equipment design while minimizing operator discomfort and long-term musculoskeletal loading (Kapse *et al.*, 2024) [30].

3.3 AI-Based Ergonomic Risk Prediction

Beyond posture recognition, artificial intelligence enables predictive ergonomic assessment by identifying complex relationships among movement patterns, workload characteristics, and physiological responses that precede the development of work-related musculoskeletal disorders. Rather than evaluating isolated postures, AI analyzes continuous streams of biomechanical and physiological data to estimate injury risk before clinical symptoms become evident (Naranjo *et al.*, 2025) ^[37].

AI-driven ergonomic assessment systems automate the calculation of established ergonomic indices, including Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA), by converting skeletal information extracted from images or motion sensors into standardized ergonomic risk scores. This automation substantially reduces observer bias, increases assessment consistency, and shortens the time required for ergonomic evaluation compared with conventional manual methods (Yang *et al.*, 2024) ^[55].

Artificial intelligence further improves biomechanical analysis through sensor fusion approaches that combine measurements obtained from inertial measurement units (IMUs), wearable motion sensors, and pressure insoles. Integration of multiple sensing modalities enables accurate estimation of spinal loading and lower back injury risk during manual material handling activities by capturing dynamic forces and postural loads that are difficult to quantify using observational techniques alone (Apicella & Tarabella, 2025; Benos *et al.*, 2020; Hilmi *et al.*, 2024) ^[5, 8, 27].

Recent developments increasingly employ hybrid deep learning architectures, particularly CNN–LSTM models, to analyze temporal changes in posture throughout complete work cycles. By incorporating both spatial posture information and temporal movement sequences, these models account for repetitive motions, cumulative fatigue, and changing workload conditions over time. Consequently, AI-based ergonomic systems progress beyond static posture evaluation toward comprehensive predictive risk management capable of supporting timely interventions and reducing the incidence of occupational musculoskeletal disorders (Yang *et al.*, 2024) ^[55].

4. Agricultural Work Systems

Agricultural work systems encompass a broad range of manual and mechanized operations that expose workers to substantial biomechanical, physiological, and environmental stresses. Although mechanization has reduced the physical demands of certain farming activities, many agricultural tasks continue to require repetitive movements, awkward body postures, heavy manual material handling, and prolonged exposure to adverse environmental conditions. These occupational demands contribute significantly to the high prevalence of work-related musculoskeletal disorders (WMSDs), making agriculture one of the most ergonomically challenging occupational sectors (Benos *et al.*, 2020; Das, 2023) ^[8, 18].

4.1 Physical Workloads

Manual agricultural activities frequently require prolonged trunk flexion, kneeling, squatting, and repetitive bending, particularly during the cultivation, harvesting, and maintenance of low-growing crops such as vegetables and strawberries. These sustained awkward postures substantially increase mechanical loading on the lumbar spine, knees, and lower extremities, thereby contributing to chronic low back pain, knee osteoarthritis, and other musculoskeletal disorders (Benos *et al.*, 2020; Das, 2023) ^[8, 18].

The repetitive nature of agricultural work further accelerates muscle fatigue and cumulative tissue damage. Continuous repetition of similar movements without sufficient recovery increases biomechanical stress on joints and soft tissues, leading to progressive deterioration of musculoskeletal health. These risks are particularly pronounced among aging agricultural workers, whose reduced physical capacity makes them more susceptible to fatigue and injury under demanding workload conditions (Benos *et al.*, 2020) ^[8].

Figure 5 illustrates representative agricultural operations characterized by repetitive manual handling, sustained bending, lifting, and prolonged awkward working postures. These activities collectively demonstrate the considerable physical demands associated with agricultural labor and highlight the importance of ergonomic interventions for reducing occupational injury risk.



Fig 5: Different agricultural activities

4.2 Manual Material Handling and Tool Use

Manual material handling (MMH) remains one of the principal contributors to musculoskeletal injury in agriculture. Agricultural workers routinely lift, carry, transport, and manipulate loads that frequently exceed 22.5 kg (50 lb) during harvesting, transportation, and storage operations. Repeated lifting of heavy loads imposes substantial mechanical stress on the spine, shoulders, wrists, and upper limbs, particularly when tasks are performed under awkward or asymmetrical body postures (Benos *et al.*, 2020; Fathallah, 2010; Sharma *et al.*, 2025; Kee, 2022) ^[8, 21, 31, 49].

The ergonomic burden associated with manual material handling is further intensified by the widespread use of traditional agricultural hand tools. Conventional implements such as sickles, pruning shears, and cutting tools often require excessive gripping force, repetitive wrist movements, and repeated elbow extension, thereby increasing cumulative loading on the upper extremities. Additionally, poor compatibility between tool dimensions and workers' anthropometric characteristics results in inefficient working postures, greater physical exertion, and elevated injury risk (Benos *et al.*, 2020; Das, 2023) ^[8, 18].

These findings emphasize the need for ergonomically designed hand tools and improved manual handling strategies that minimize excessive physical loading while enhancing worker comfort and operational efficiency.

4.3 Tractor and Machinery Operation

Although agricultural mechanization has substantially improved farm productivity, it has also introduced new categories of ergonomic hazards. Tractor operation, in particular, has been consistently identified as a major contributor to musculoskeletal disorders because operators are frequently required to maintain constrained sitting postures while simultaneously performing multiple visual and manual tasks (Benos *et al.*, 2020; Fathallah, 2010) ^[8, 21].

During routine field operations, tractor operators repeatedly rotate the neck and trunk to monitor rear-mounted implements while simultaneously manipulating steering controls, transmission systems, and dashboard interfaces. These sustained twisting postures increase loading on the cervical spine, shoulders, and lower back, particularly during prolonged working periods (Benos *et al.*, 2020; Grandi *et al.*, 2022) ^[8, 23].

Ergonomic deficiencies in cabin design further contribute to operator discomfort. Poorly positioned control panels, limited adjustability of seats and dashboards, and intrusive cabin layouts restrict natural body movement and promote awkward working postures. Similarly, digital displays incorporated into semi-automated agricultural machinery may adversely affect posture when viewing angles require excessive head rotation or prolonged neck extension, leading to increased muscular activation and long-term musculoskeletal strain (Grandi *et al.*, 2022; Vitale *et al.*, 2024) ^[23, 53].

These observations demonstrate the importance of incorporating ergonomic principles into the design of agricultural machinery to improve operator comfort, reduce physical workload, and minimize long-term occupational health risks.

4.4 Environmental Exposures

Agricultural workers are routinely exposed to multiple environmental hazards that adversely affect both physical health and ergonomic performance. Among these, prolonged exposure to elevated temperatures and solar radiation is particularly significant, frequently resulting in dehydration, heat exhaustion, heat stroke, and cumulative physiological stress during intensive

field operations, especially under summer conditions (Kee, 2022; Petrosyan *et al.*, 2020; Ross *et al.*, 2016) ^[31, 40, 44].

Mechanized agricultural operations introduce additional physical stressors through continuous exposure to whole-body vibration (WBV) generated by tractor engines and uneven terrain. Long-term WBV exposure has been strongly associated with chronic lower back pain, spinal degeneration, and reduced operator comfort. Likewise, prolonged use of handheld powered equipment exposes workers to hand-arm transmitted vibration (HATV), increasing the likelihood of vibration-induced white finger syndrome and neuromuscular impairments affecting the upper extremities (Benos *et al.*, 2020) ^[8].

The agricultural working environment may also present additional occupational hazards associated with inadequate workplace conditions. Poor ventilation and insufficient illumination within agricultural buildings, including curing barns and enclosed farm structures, increase the likelihood of slips, falls, and traumatic injuries. Furthermore, tractor-mounted implements and agricultural machinery frequently generate noise levels exceeding 85 dB(A), exposing workers to hearing impairment, fatigue, irritability, and increased cardiovascular stress during prolonged operation (Schuman, 2002; Martins *et al.*, 2014; Mushtaq *et al.*, 2025) ^[33, 36, 48].

Collectively, these physical, mechanical, and environmental stressors illustrate the multifactorial nature of ergonomic risks within agricultural work systems. Effective occupational health management therefore requires integrated assessment approaches that simultaneously consider biomechanical loading, environmental exposures, and worker physiology to support comprehensive ergonomic risk reduction.

5. Digital Technologies Used in Agricultural Ergonomics

The advancement of Agriculture 4.0 has accelerated the integration of digital technologies into ergonomic assessment, enabling continuous monitoring of workers and proactive management of occupational health risks. Unlike conventional observational methods, digital ergonomic technologies collect and analyze biomechanical, physiological, and environmental information in real time, allowing ergonomic interventions to be implemented before injuries occur. The principal technologies include wearable sensors, computer vision systems, motion capture technologies, digital twins, virtual prototyping, robotics, and human-robot collaboration, all of which contribute to data-driven ergonomic management within modern agricultural systems (Apicella & Tarabella, 2025) ^[5].

5.1 Wearable Sensors and IoT-Based Monitoring

Wearable sensing technologies constitute one of the most mature and widely implemented components of digital ergonomics. By integrating workers into Internet of Things (IoT)-based monitoring systems, wearable devices continuously acquire physiological and biomechanical information, enabling real-time assessment of physical workload, posture, fatigue, and environmental exposure. This approach transforms agricultural workers into active data sources within smart farming ecosystems, thereby facilitating predictive occupational health management (Apicella & Tarabella, 2025; Donisi *et al.*, 2022) ^[5, 19]. A wide range of wearable technologies has been adopted for agricultural ergonomic assessment. Inertial Measurement Units (IMUs), accelerometers, gyroscopes, and biopotential sensors such as surface electromyography (sEMG) quantify body movements, joint orientations, angular velocity, and muscular activity during agricultural operations. These devices provide objective measurements of worker posture and physical

workload while supporting continuous evaluation of musculoskeletal stress under field conditions.

Wearable systems are also employed for physiological monitoring. Biometric bands and sensor-integrated garments continuously record heart rate, body temperature, heat stress, and other physiological responses associated with physical exertion. Environmental sensors complement these measurements by monitoring workplace conditions, including exposure to hazardous gases such as ammonia, thereby enabling comprehensive evaluation of occupational health risks.

The information acquired by wearable devices is transmitted through IoT-enabled communication networks to cloud-based monitoring platforms, where machine learning algorithms analyze sensor streams to classify worker activities, detect abnormal movements, and identify potential safety risks. For example, SHIMMER3-based wearable systems have demonstrated the ability to distinguish accidental falls from routine agricultural activities, while integrated monitoring dashboards provide immediate visual or auditory alerts whenever hazardous conditions are detected (Apicella & Tarabella, 2025; Donisi *et al.*, 2022) ^[5, 19].

Table 1 summarizes representative wearable technologies used in agricultural ergonomics, together with their monitored parameters, technological components, application domains, and functional outputs. These examples demonstrate the diversity of wearable solutions currently available for improving worker safety, health monitoring, and ergonomic evaluation.

5.2 Computer Vision and Image-Based Posture Assessment

Computer vision (CV) has become an increasingly important technology for ergonomic assessment because it enables objective posture evaluation without requiring workers to wear body-mounted sensors. This noninvasive approach is particularly advantageous in agricultural environments, where wearable devices may interfere with manual operations or become uncomfortable during prolonged outdoor work (MassirisFernández *et al.*, 2020) ^[34].

Modern computer vision systems employ deep learning algorithms, particularly Convolutional Neural Networks (CNNs), to estimate human body posture directly from digital images or video sequences. By automatically identifying anatomical landmarks and constructing digital skeletal models, these systems provide quantitative measurements of body posture that support objective ergonomic evaluation.

Among the available pose estimation models, MoveNet has demonstrated considerable effectiveness in agricultural applications. The model extracts anatomical key points and classifies trunk posture into neutral, slight forward bending, and full forward bending categories, achieving posture classification accuracies of approximately 87.8% when combined with Artificial Neural Networks (ANNs). Such performance illustrates the capability of AI- assisted computer vision to identify potentially harmful working postures during actual agricultural operations (Kapse *et al.*, 2024) ^[30].

Table 1: Wearable Device Technologies, Applications, and Functional Outputs

Device Type	Measured Parameter	Technologies Employed	Application Domain	Functional Output	Authors
Smart glasses	Visual stimuli (AR)	AR display, Inertial sensors	Animal husbandry – Precision livestock farming	Worker assistance, identification, and communication support	Caria <i>et al.</i> , 2019 ^[11]
Sensors for hand, wrist, and forearm	Upper limb joint angles	ESP32, IMU, Bluetooth BLE, LCD, Kalman filter	Viticulture – Pruning simulation	Postural risk assessment and ergonomic feedback	Cividino <i>et al.</i> , 2024 ^[16]
Inertial band for wrist	Three-dimensional movements (quaternions)	IMU, LoRa, HTM, SDR	Smart farming – Predictive safety	Fall detection and activity monitoring with safety alerts	Adhitya <i>et al.</i> , 2023 ^[2]
Waistband	Acceleration, angular velocity	SHIMMER3, Bluetooth, ML (kNN, SVM, ANN)	Agriculture – Simulated activities	Movement tracking, activity recognition, and fall detection	Son <i>et al.</i> , 2022 ^[52]
Aerogel sensor for face (mask)	Exhaled air humidity	AuNPs, PNIPAm	Health – Intelligent machine respiration monitoring	Real-time breath monitoring and voice recognition	Ali <i>et al.</i> , 2018 ^[3]
IMU sensors for chest, spine, and wrists	Acceleration, angular velocity, magnetic field	IMU, LSTM	Agriculture – Human–robot collaboration	Recognition of agricultural work activities	Anagnostis <i>et al.</i> , 2021 ^[4]
Sensor patches – chest, forearm	Trunk inclination, muscle strain	Accelerometer, ECG, IMU, Sensors	Viticulture – Manual pruning	Posture assessment and pruning task monitoring	Arrais <i>et al.</i> , 2023 ^[6]
Arm bands	Temperature, humidity, noise, light, heart rate	Environmental sensors, alert-enabled band, cloud integration	Agriculture – Field activities	Environmental and physiological monitoring with alerts	Cannady <i>et al.</i> , 2025 ^[9]
Elastic suit	Lumbar torque, EMG	Active band, wireless EMG, dynamometer	Agriculture – Simulated lifting	Lumbar strain reduction and MSD prevention	Cha <i>et al.</i> , 2021 ^[13]
Wrist/arm band	Distance between operators (COVID-19 contact tracing)	Bluetooth, GPS, NFC, cloud	Viticulture – Manual pruning	Proximity monitoring and contact-tracing alerts	Catania <i>et al.</i> , 2022 ^[12]
Lumbar support exoskeleton	– (no direct measurement)	IMU, EMG	Agriculture – Manual material handling	Lower-back load reduction and ergonomic support	Chittar and Barve, 2022 ^[14]
Printable sensor	Ammonia concentration in the air	SWCNT, Nafion, PET-based printing, Arduino	Agriculture – Environmental exposure	Rapid ammonia gas detection and exposure monitoring	Hall <i>et al.</i> , 2024 ^[25]
Body-worn RFID module	Operator position and proximity	RFID, WSAN, GPS/GNSS	Agriculture – Remote operation of mobile machinery	Operator tracking and workplace safety monitoring	Pirozzi <i>et al.</i> , 2020 ^[41]
Sensorized jacket for the chest	Height, trunk inclination, acceleration, magnetic field	SHIMMER3, MLP	Logistics – Lifting and handling	Lifting activity recognition and biomechanical risk assessment	Pistolesi and Lazzerini, 2020 ^[42]

Computer vision systems also automate traditional ergonomic assessment methods by calculating joint angles from skeletal models and converting them into standardized ergonomic indices such as Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA). Unlike manual observational techniques, AI-based image analysis enables continuous monitoring of multiple workers simultaneously under practical field conditions, including environments

characterized by variable illumination, partial obstruction, and unstable camera viewpoints. Consequently, computer vision provides an efficient, scalable, and objective alternative for ergonomic risk assessment within agricultural work systems. Figure 6 presents representative trunk posture classifications generated using the MoveNet-based posture estimation framework (Kapse *et al.*, 2024; Yang *et al.*, 2024) [30, 55].

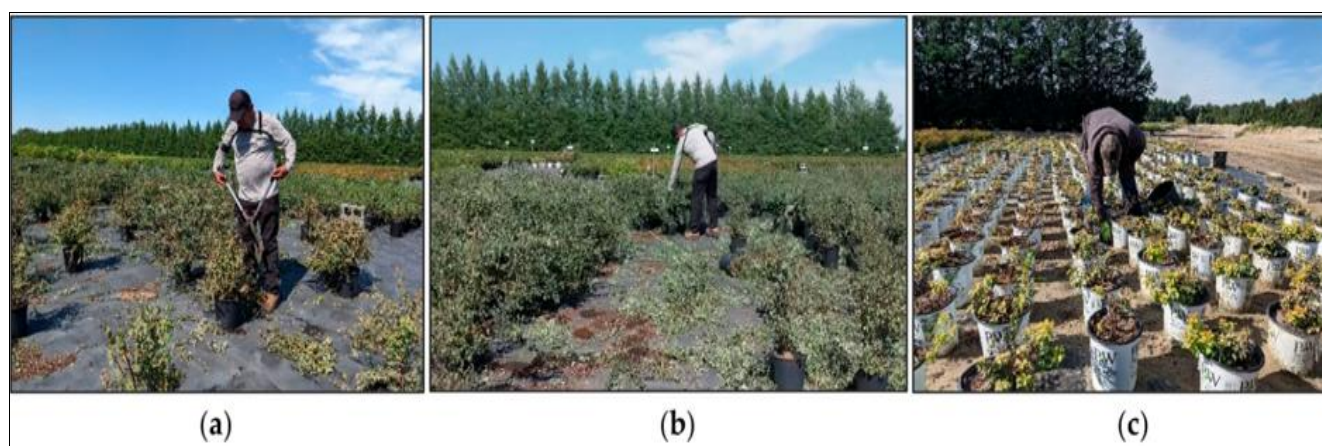


Fig 6: Sample images displaying different trunk posture classes: (a) Neutral Posture, (b) Half Bend Posture, and (c) Full Bend Posture

5.3 Motion Capture Systems

Motion capture (MoCap) technologies provide highly accurate digital representations of human movement and are regarded as one of the most objective methods for ergonomic assessment. Unlike observational approaches, motion capture systems quantify body kinematics directly, enabling comprehensive biomechanical analysis of complex agricultural tasks (Rybníkář *et al.*, 2023) [45].

Motion capture technologies are broadly categorized into marker-based and marker-less systems. Marker-based systems employ reflective markers attached to the worker's body, whereas marker-less approaches utilize intelligent camera systems to estimate body posture without physical markers. Both approaches provide detailed measurements of body segment orientation, joint motion, and movement frequency during agricultural operations (Salisu *et al.*, 2023; Yang *et al.*, 2024) [47, 55]. Wearable inertial motion capture systems, including Xsens, integrate multiple inertial sensors distributed across different body segments to monitor orientation, acceleration, and movement at sampling frequencies approaching 120 Hz. Such systems have been applied to agricultural activities including banana harvesting and grapevine pruning, allowing researchers to quantify repetitive movements, joint amplitudes, and extreme working postures associated with elevated musculoskeletal risk (Merino *et al.*, 2019) [35].

By converting human movement into digital datasets that can be stored, replayed, and analyzed quantitatively, motion capture systems facilitate identification of critical joint angles and repetitive movement patterns associated with occupational injury. This capability provides valuable support for ergonomic intervention, equipment redesign, and worker training (Rybníkář *et al.*, 2023) [45].

5.4 Digital Twins and Virtual Prototypes for Farm Work Design

Digital Twin (DT) technology enables the creation of virtual representations of physical systems that continuously simulate real-world behavior. Within agricultural ergonomics, Digital Twins provide a powerful platform for evaluating equipment design, work processes, and human-machine interactions before physical implementation, thereby reducing development costs while improving worker safety (Slob *et al.*, 2023; Peladarinos *et al.*, 2023) [39, 51].

Digital Human Modeling (DHM) (Fig. 7) integrated with Computer-Aided Design (CAD) allows ergonomic principles to be incorporated during the earliest stages of agricultural equipment development. Virtual human manikins, including the Jack manikin, simulate manual agricultural operations within three-dimensional environments, enabling designers to evaluate visibility, reachability, working posture, and ergonomic indices such as EAWS before constructing physical prototypes (Caputo *et al.*, 2019; Naranjo *et al.*, 2025) [10, 37].

These technologies have proven particularly valuable for optimizing tractor cabins and operator workstations. Virtual simulations evaluate the accessibility of controls, operator visibility, and overall driver comfort across workers with different anthropometric characteristics, thereby facilitating inclusive and human-centered equipment design (Patel *et al.*, 2016; Salisu *et al.*, 2023) [38, 47].

Beyond machinery design, Digital Twin technology has been extended to greenhouse horticulture, where virtual environments enable farmers to visualize production systems, monitor crop development remotely, and evaluate operational strategies through Virtual Reality (VR). These digital environments provide opportunities to identify ergonomic and operational inefficiencies within risk-free simulation platforms before implementation under actual field conditions (Slob *et al.*, 2023; Peladarinos *et al.*, 2023) [39, 51].

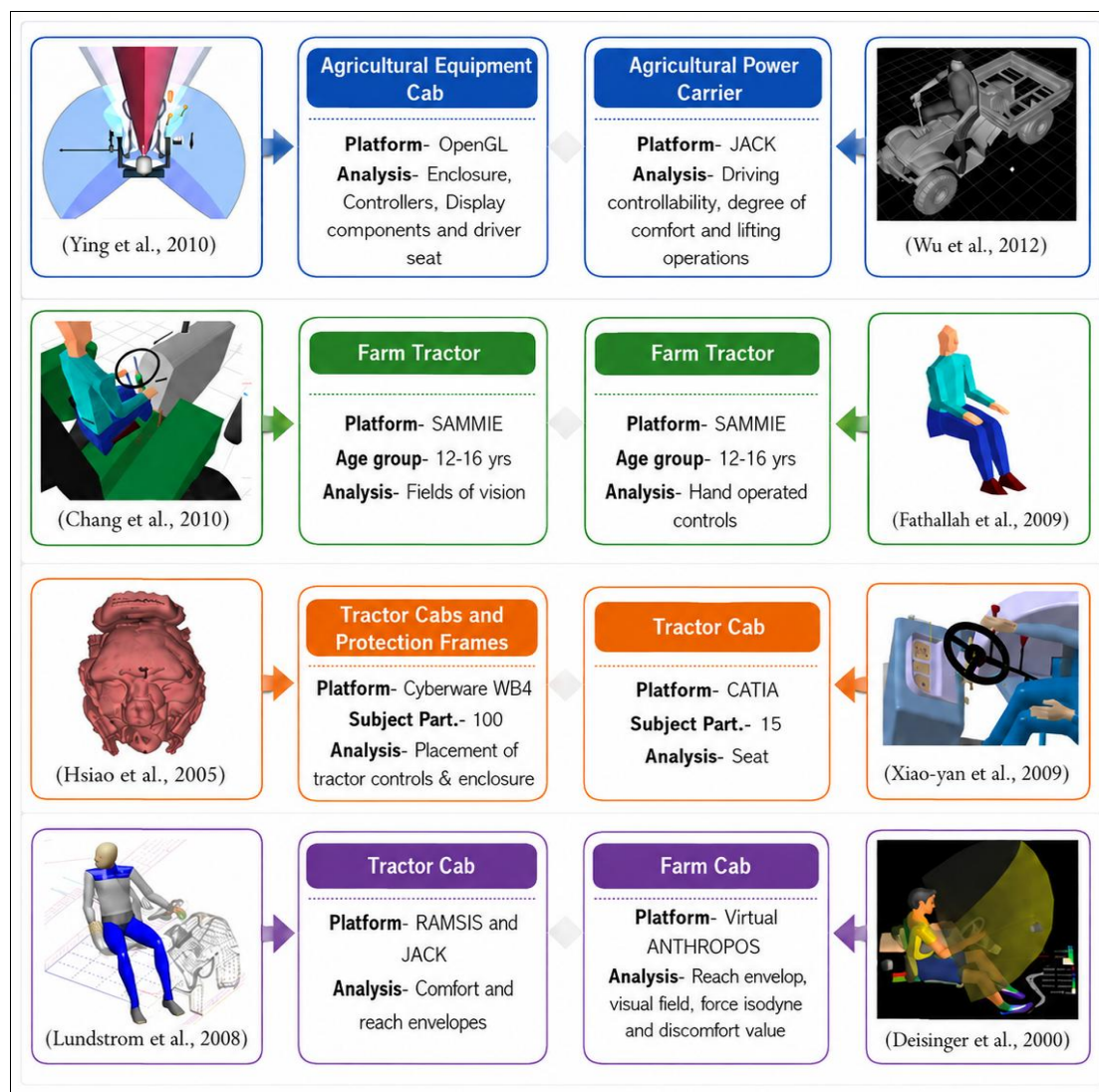


Fig 7: Pictorial representation of DHM applications in agriculture

5.5 Robotics and Automation as Ergonomic Interventions

Robotics and automation represent an important strategy for reducing worker's exposure to physically demanding agricultural tasks. Rather than replacing human labor entirely, modern robotic systems increasingly function as collaborative technologies that complement workers during activities associated with repetitive movements, heavy lifting, and awkward postures (Adamides & Edan, 2023) ^[1].

Collaborative robots (cobots) operate alongside agricultural workers within shared workspaces, assuming responsibility for physically intensive activities such as transporting harvested produce and carrying heavy crates. By reducing repetitive lifting and prolonged bending, cobots substantially decrease physical workload while lowering the risk of work-related musculoskeletal disorders (Adamides & Edan, 2023) ^[1].

Exoskeletons have emerged as another promising ergonomic intervention. Both passive and active exoskeleton systems provide mechanical assistance during lifting, overhead work, and manual material handling, thereby reducing muscle activation and perceived physical exertion in the lower back and shoulders. These wearable assistive technologies have demonstrated considerable potential for minimizing fatigue and preventing musculoskeletal injury during physically demanding agricultural operations (Naranjo *et al.*, 2025; Hilmi *et al.*, 2024) ^[27, 37]. Automation has also reduced ergonomic risks associated with repetitive manual operations. GPS-guided automated

weeding systems eliminate prolonged stooping during weed removal, while advanced human-robot collaboration systems employ intelligent control algorithms capable of predicting hazardous situations and adapting robot behavior accordingly. Complementary wearable haptic interfaces further improve worker safety by providing immediate vibration-based feedback whenever unfavorable postures are detected (Fathallah, 2010; Hilmi *et al.*, 2024) ^[21, 27].

6. AI-Based Ergonomic Evaluation Methods

Artificial intelligence has fundamentally transformed ergonomic assessment by enabling automated, objective, and predictive evaluation of occupational risks. Unlike conventional observation-based methods, AI-driven ergonomic systems integrate machine learning, deep learning, wearable sensing, computer vision, and cloud computing to continuously analyze worker posture, movement, and physiological responses. These approaches improve assessment accuracy, reduce observer bias, and facilitate timely ergonomic interventions that minimize the occurrence of work-related musculoskeletal disorders (WMSDs) (Naranjo *et al.*, 2025; Yang *et al.*, 2024) ^[37, 55].

6.1 Machine Learning Models for Ergonomic Risk Classification

Machine learning (ML) algorithms have become central to the automatic classification of ergonomic risks by replacing

subjective observational assessments with objective, data-driven decision-making. These algorithms learn relationships between biomechanical variables and ergonomic risk levels, allowing continuous classification of worker posture with high precision across diverse agricultural tasks (Kapse *et al.*, 2024) ^[30].

Several supervised learning algorithms have demonstrated strong performance in ergonomic risk assessment, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN). These models classify working postures into standardized ergonomic risk categories using features extracted from wearable sensors, computer vision systems, or motion capture technologies. Their ability to process large datasets enables rapid identification of hazardous working conditions while substantially reducing observer variability associated with conventional ergonomic assessment methods.

Among the reported applications, a posture assessment framework integrating MoveNet with Artificial Neural Networks achieved a posture classification accuracy of approximately 87.8% during outdoor nursery operations. Similarly, ANN-based monitoring systems used in industrial assembly processes reported approximately 95% accuracy for detecting defective operational conditions through vibration and force analysis. Random Forest algorithms have also demonstrated superior performance in classifying biomechanical risks according to the Revised NIOSH Lifting Equation, frequently achieving classification accuracies exceeding 90% (Donisi *et al.*, 2022; Naranjo *et al.*, 2025) ^[19, 37].

Machine learning applications have further expanded to portable ergonomic assessment systems. Smartphone based solutions mounted on the upper arm utilize embedded sensors and machine learning algorithms to classify ergonomic risks during occupational activities with reported accuracy of approximately 90.2%. In addition, Probabilistic Neural Networks (PNNs) have been employed to evaluate dynamic changes in biomechanical workload throughout complete work cycles, thereby extending ergonomic assessment beyond static posture evaluation toward continuous monitoring of occupational risk (Yang *et al.*, 2024; Naranjo *et al.*, 2025) ^[37, 55].

6.2 Deep Learning for Human Pose Estimation

Deep learning has substantially advanced ergonomic posture analysis by enabling automatic extraction of complex spatial features from images and video sequences without manual feature engineering. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have become the dominant architectures for human pose estimation because of their ability to identify anatomical landmarks accurately while accommodating the variability associated with agricultural work environments (Yang *et al.*, 2024) ^[55].

State-of-the-art pose estimation frameworks, including OpenPose and MoveNet, identify two-dimensional or three-dimensional skeletal key points directly from digital images or video streams. These algorithms generate digital skeletal models from which joint angles, body orientation, and movement characteristics can be computed automatically, thereby facilitating objective ergonomic assessment without requiring specialized motion capture equipment (Kapse *et al.*, 2024; MassirisFernández *et al.*, 2020) ^[34].

Among these approaches, MoveNet has attracted particular attention because of its lightweight architecture and computational efficiency, making it suitable for deployment on resource constrained devices commonly used in agricultural environments. As illustrated in Figure 8, the model identifies

anatomical landmarks represented by key points and connects them to generate a complete skeletal representation of worker posture. Visible body segments are represented by yellow lines, whereas predicted but non-visible body segments are indicated by purple lines based on learned spatial relationships among anatomical landmarks (Kapse *et al.*, 2024) ^[30].



Fig 8: Output of MoveNet for Human Posture Estimation

The circles are anatomical key points, and the lines connected between some of the key points. The yellow lines are the visible ones, and the purple lines are not visible but predicted.

The skeletal information generated by deep learning models provides the basis for automatic calculation of established ergonomic assessment indices, including Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA). Hybrid deep learning architectures, such as Spatial Temporal Graph Convolutional Networks (ST-GCN), further improve posture estimation by compensating for skeleton loss or incorrect joint detection caused by limb overlap and occlusion. More recently, deep neural networks capable of reconstructing three-dimensional body posture from conventional two-dimensional images have emerged as cost-effective alternatives to conventional motion capture systems, expanding the applicability of AI-driven ergonomic assessment within agricultural environments (Yang *et al.*, 2024; Massiris Fernández *et al.*, 2020) ^[34, 55].

6.3 AI-Enabled Decision Support Systems

Artificial intelligence has expanded the scope of ergonomic assessment beyond posture recognition toward intelligent decision support capable of assisting both equipment designers and farm managers. AI-enabled Decision Support Systems (DSS) integrate biomechanical analysis with predictive analytics to recommend ergonomic improvements before hazardous conditions develop, thereby supporting proactive occupational health management (Grandi *et al.*, 2022) ^[23].

One important application involves fuzzy logic-based decision support systems, which convert three-dimensional joint angle measurements into continuous ergonomic risk levels using rule-based inference rather than discrete scoring systems. Compared with conventional integer-based ergonomic indices, fuzzy logic provides smoother transitions between risk categories and more realistic representation of gradual posture changes encountered during agricultural work (Yang *et al.*, 2024; Hilmi *et al.*, 2024) ^[27, 55]. Artificial intelligence also strengthens Digital Human Modeling (DHM) by integrating predictive analysis into virtual design environments. Within these systems, designers simulate

agricultural tasks using virtual prototypes and evaluate the physical demands associated with different workstation layouts, machinery configurations, and equipment dimensions before physical implementation. Such capabilities facilitate early identification and correction of ergonomic deficiencies, reducing development costs while improving worker safety (Naranjo *et al.*, 2025; Caputo *et al.*, 2019) ^[10, 37].

Beyond equipment design, AI-driven decision support systems contribute to predictive occupational health management by identifying movement patterns associated with elevated injury risk. Within collaborative agricultural environments, AI algorithms optimize the movement of collaborative robots (cobots) to reduce worker exposure to hazardous tasks while simultaneously providing workers with immediate visual or haptic feedback whenever unsafe postures are detected. These capabilities facilitate continuous behavioral correction and proactive ergonomic intervention during routine agricultural operations (Apicella & Tarabella, 2025; Naranjo *et al.*, 2025) ^[5, 37].

6.4 Integration of Artificial Intelligence with Wearables and IoT Platforms

The integration of artificial intelligence with wearable sensing technologies and Internet of Things (IoT) platforms has created comprehensive digital ecosystems capable of continuous occupational health monitoring. Within these systems, wearable devices collect biomechanical and physiological measurements that are transmitted to cloud-based analytical platforms, where AI algorithms perform predictive ergonomic analysis in real time (Naranjo *et al.*, 2025) ^[37].

Wearable devices such as Inertial Measurement Units (IMUs), pressure insoles, and physiological sensors continuously monitor worker posture, movement, and physical workload. Industrial IoT gateways provide communication between field devices and cloud-based analytical services, enabling centralized storage, processing, and visualization of ergonomic data. AI models operating within these cloud environments generate individualized ergonomic assessments while identifying patterns associated with developing musculoskeletal disorders (Apicella & Tarabella, 2025; Hilmi *et al.*, 2024; Yang *et al.*, 2024) ^[5, 27, 55]. The combination of AI, IoT, and Digital Twin technology further enhances ergonomic management by integrating real-time wearable sensor data into virtual representations of workers and agricultural systems. These Digital Twins provide personalized recommendations and early warning notifications whenever physiological or biomechanical indicators suggest increasing occupational risk (Peladarinos *et al.*, 2023) ^[39].

Recent developments have also incorporated smartphone-based ergonomic assessment systems that combine high-definition cameras with cloud-based AI models to provide immediate posture evaluation and corrective feedback. The adoption of high-speed communication technologies, particularly 5G, supports low-latency transmission of large sensor datasets, ensuring stable real-time operation of integrated ergonomic monitoring systems across modern agricultural environments (Yang *et al.*, 2024) ^[55].

7. Applications of Digital Ergonomics in Agricultural Tasks

The practical implementation of digital ergonomics has demonstrated considerable potential for reducing occupational risks across a wide range of agricultural operations. By integrating wearable sensing technologies, artificial intelligence (AI), computer vision, Digital Human Modeling (DHM), robotics, and Human-Robot Collaboration (HRC), digital

ergonomic systems enable continuous monitoring of workers while reducing physical workload during labor-intensive agricultural tasks. Current applications are particularly prominent in harvesting, pruning, planting, and weeding operations, where repetitive movements, awkward postures, and manual material handling represent major ergonomic challenges (Apicella & Tarabella, 2025; Benos *et al.*, 2020) ^[5, 8].

7.1 Harvesting and Picking Tasks

Harvesting is widely recognized as one of the most physically demanding agricultural operations because it requires repetitive reaching, prolonged bending, overhead work, heavy manual handling, and sustained awkward body postures. These occupational demands substantially increase the risk of work-related musculoskeletal disorders, particularly affecting the lower back, shoulders, neck, and upper limbs (Benos *et al.*, 2020) ^[8].

Wearable Motion Capture Systems

Wearable motion capture technologies have been extensively employed to quantify biomechanical loading during harvesting activities. Inertial motion capture systems such as Xsens continuously record body posture, joint movements, and movement frequencies while workers perform harvesting operations. These systems provide objective biomechanical measurements that facilitate identification of repetitive movements and awkward working postures associated with elevated musculoskeletal risk (Merino *et al.*, 2019) ^[35].

Applications in banana harvesting have demonstrated the capability of wearable motion capture systems to identify excessive trunk flexion, shoulder abduction, and repetitive upper-limb movements resulting from handling large and heavy banana bunches. Such biomechanical analyses provide quantitative evidence that supports ergonomic redesign of harvesting methods and equipment (Merino *et al.*, 2019) ^[35].

Human-Robot Collaboration

Human-Robot Collaboration (HRC) has emerged as an effective strategy for reducing the physical demands associated with harvesting operations. Rather than replacing workers entirely, collaborative robots (cobots) assist agricultural workers by transporting harvested produce and carrying heavy loads throughout the harvesting process. This approach substantially reduces repetitive lifting, prolonged carrying, and frequent bending, thereby decreasing physical workload while simultaneously improving harvesting efficiency (Adamides & Edan, 2023) ^[1].

Within collaborative harvesting systems, workers continue to perform tasks requiring human judgment and ability, whereas cobots assume responsibility for repetitive material transportation. This complementary distribution of labor minimizes musculoskeletal loading without compromising operational productivity and represents an important step toward human-centered automation in Agriculture 4.0 (Adamides & Edan, 2023) ^[1].

Ergonomic Harvesting Platforms

Mechanical harvesting aids have also been developed to reduce ergonomic risks during fruit and vegetable harvesting. Motorized picking platforms eliminate the need for ladders and substantially reduce prolonged overhead reaching, repetitive climbing, and carrying of heavy collection bags. Consequently, these platforms decrease the likelihood of falls while minimizing asymmetric spinal loading associated with conventional

harvesting practices (Fathallah, 2010) ^[21].

Compared with traditional harvesting methods, ergonomic harvesting platforms improve worker safety while simultaneously increasing harvesting efficiency by reducing unnecessary physical movements and shortening transportation distances during produce collection.

Digital Ergonomic Assessment During Harvesting

The integration of wearable sensing technologies, motion capture systems, and artificial intelligence enables continuous ergonomic monitoring throughout harvesting operations. Real-time posture analysis allows early identification of hazardous movements and cumulative physical loading, facilitating timely ergonomic interventions before musculoskeletal injuries occur. Such objective biomechanical assessment provides valuable guidance for optimizing harvesting techniques, equipment design, and work organization while promoting long-term occupational health.

7.2 Weeding and Planting Tasks

Weeding and planting operations are characterized by prolonged stooping, repetitive upper-limb movements, kneeling, squatting, and sustained trunk flexion, making them among the most ergonomically demanding agricultural activities. Continuous exposure to these awkward postures contributes substantially to lower back pain, knee disorders, and muscular fatigue, particularly when work is performed under unfavorable ground conditions (Benos *et al.*, 2020) ^[8].

Automated Weeding Systems

Artificial intelligence has facilitated the development of automated weeding technologies that substantially reduce the need for manual weed removal. GPS-guided computer vision systems accurately identify crop rows and distinguish cultivated plants from weeds using digital image analysis. Automatic weed knives subsequently remove unwanted vegetation with minimal human intervention, thereby reducing repetitive manual weeding and limiting worker exposure to herbicides (Fathallah, 2010) ^[21]. Automation not only decreases physical workload but also improves operational precision by enabling targeted weed removal while minimizing crop damage. Consequently, AI-assisted weeding systems contribute simultaneously to improved ergonomic conditions and enhanced agricultural productivity.

Digital Human Modeling for Tool Design

Digital Human Modeling (DHM) combined with Computer-Aided Design (CAD) has become an effective approach for optimizing agricultural hand tools used during planting and weeding. Virtual ergonomic simulations enable designers to evaluate worker posture while manipulating different tool geometries, facilitating the development of equipment that better matches workers' anthropometric characteristics (Patel *et al.*, 2016) ^[38].

For example, DHM-based simulations have demonstrated that appropriately designed long-handled hoes substantially reduce trunk flexion during manual weeding operations. By improving tool dimensions before physical manufacturing, digital ergonomic design minimizes physical strain while simultaneously enhancing worker productivity and comfort (Benos *et al.*, 2020; Patel *et al.*, 2016) ^[8, 38].

Real-Time Monitoring Under Challenging Field Conditions

Agricultural planting frequently occurs under difficult environmental conditions that influence worker biomechanics.

Investigations of rice transplantation have shown that muddy terrain significantly increases lower-extremity muscular activity and physical discomfort because workers must continuously stabilize themselves while maintaining awkward working postures (Apicella & Tarabella, 2025) ^[5].

Digital ergonomic monitoring systems incorporating wearable sensors and computer vision enable continuous assessment of worker posture under these challenging conditions. Real-time biomechanical feedback facilitates early identification of excessive physical loading while supporting the implementation of protective equipment and ergonomic interventions that reduce environmental risk factors during planting operations (Benos *et al.*, 2020; Apicella & Tarabella, 2025) ^[5, 8].

Assistive Wearable Technologies

Wearable assistive technologies have recently been investigated for reducing physical workload during repetitive digging and planting activities. Personal assist suits and lower-back exoskeletons provide mechanical assistance to the lumbar region during repeated bending, decreasing activation of the lumbar erector spinae muscles while promoting more stable movement patterns throughout work activities (Apicella & Tarabella, 2025) ^[5]. These wearable assistive systems demonstrate the growing role of human-centered technologies in minimizing musculoskeletal loading during labor-intensive agricultural operations. Continued improvements in comfort, flexibility, and usability are expected to further enhance their practical applicability within modern agricultural work systems.

8. Benefits of Digital and AI-Based Ergonomics in Agriculture

Digital technologies and AI are transforming agricultural ergonomics by enabling continuous monitoring, predictive risk assessment, and data-driven decision-making. These advancements enhance worker safety, improve equipment design, and increase operational efficiency. They also support training and long-term occupational health management in agricultural environments (Apicella & Tarabella, 2025; Naranjo *et al.*, 2025) ^[5, 37].

8.1 Enhanced Occupational Health and Injury Prevention

Wearable sensors, IoT devices, and exoskeletons enable continuous monitoring of posture, fatigue, muscle activity, and environmental risks such as heat stress. Early detection of ergonomic hazards allows timely corrective actions and reduces musculoskeletal disorders. These systems significantly improve worker safety and long-term health outcomes in agriculture (Kapse *et al.*, 2024; Yang *et al.*, 2024) ^[30, 55].

8.2 Objective Ergonomic Risk Assessment

AI, wearable technologies, and computer vision systems provide real-time and objective ergonomic evaluations. They reduce observer bias by analyzing posture, movement patterns, and biomechanical loads with high accuracy. Continuous monitoring ensures more reliable risk assessment across diverse agricultural tasks and conditions (Massiris-Fernández *et al.*, 2020; Hilmi *et al.*, 2024) ^[27, 34].

8.3 Digital Human Modeling and Virtual Prototyping

Digital Human Modeling (DHM) and CAD-based simulations enable ergonomic evaluation of tools and machinery before physical production. These virtual environments improve safety, usability, and comfort while reducing design costs. They also allow adaptation to diverse worker anthropometry and

agricultural conditions (Slob *et al.*, 2023; Peladarinos *et al.*, 2023) ^[39, 51].

8.4 Operational Efficiency and Decision Support

AI systems, collaborative robots, and Digital Twin technologies optimize agricultural workflows and reduce physical workload. They enhance resource allocation, improve productivity, and support real-time decision-making. These technologies ensure efficiency while maintaining worker health and safety (Adamides & Edan, 2023; Naranjo *et al.*, 2025) ^[1, 37].

8.5 Real-Time Feedback and Skills Development

AI-based systems provide immediate feedback to correct unsafe postures and reduce injury risk during work. Virtual Reality (VR) environments offer safe and immersive training for agricultural tasks. Together, these tools enhance ergonomic awareness, skill development, and long-term occupational safety (Hilmi *et al.*, 2024; Slob *et al.*, 2023) ^[27, 51].

9. Challenges and Limitations

9.1 Technical and Environmental Challenges

Agricultural environments expose digital ergonomic systems to dust, rain, heat, uneven terrain, and variable lighting, which reduce sensor reliability and computer vision accuracy. Occlusion from crops, tools, and machinery further affects posture detection and ergonomic risk estimation. Wearable sensors may also experience motion artifacts and unstable wireless connectivity during field use. These factors limit continuous and accurate monitoring in real-world conditions. Therefore, robust sensor fusion and improved AI models are required for reliable performance (Apicella & Tarabella, 2025; Naranjo *et al.*, 2025) ^[5, 37].

9.2 Artificial Intelligence and Data Constraints

AI-based ergonomic systems require large, diverse, and well-annotated datasets, which are often unavailable in agricultural contexts. Deep learning models also demand high computational resources, limiting deployment on portable or edge devices. Many general pose estimation models include unnecessary body landmarks, reducing efficiency for task-specific analysis. Developing lightweight AI architectures and agriculture specific datasets is therefore essential. These improvements will enhance scalability and practical usability in farming environments (Kapse *et al.*, 2024; Yang *et al.*, 2024) ^[30, 55].

9.3 Physical and Usability Limitations

Wearable ergonomic technologies, such as exoskeletons, are often heavy, uncomfortable, and may restrict natural movement during prolonged agricultural tasks. Virtual Reality (VR) systems can also cause motion sickness, dizziness, and visual fatigue with extended use. Additionally, there is a lack of standardized guidelines for implementing these technologies across different farming operations. Improving ergonomics, comfort, and usability is essential to increase worker acceptance. User-centered design approaches are therefore critical for successful adoption (Hilmi *et al.*, 2024; Slob *et al.*, 2023) ^[27, 51].

9.4 Socioeconomic and Infrastructural Barriers

High costs of AI systems, robotics, wearable devices, and VR technologies significantly limit adoption, especially among small-scale farmers. Many rural areas also lack reliable internet connectivity and digital infrastructure required for real-time monitoring systems. Cultural resistance, privacy concerns, and low technological trust further hinder acceptance. These challenges highlight the need for affordable, scalable, and

farmer-friendly solutions. Policy support and inclusive implementation strategies are essential for wider adoption (Apicella & Tarabella, 2025; Naranjo *et al.*, 2025) ^[37].

9.5 Methodological Limitations in Existing Research

Most existing studies rely on short-term laboratory experiments, which do not fully represent real agricultural working conditions. Seasonal variations, long-term fatigue, and cumulative musculoskeletal load are often not considered. There is also limited large-scale field validation of digital ergonomic systems. This restricts the generalizability of current findings. Future research should focus on long-term, real-world, and multidisciplinary field studies to validate effectiveness in agriculture (Massiris-Fernández *et al.*, 2020; Peladarinos *et al.*, 2023) ^[34, 39].

10. Future Research Directions

Future research should focus on transforming digital ergonomics from experimental technologies into practical, field-validated solutions for agriculture. Although advances have been made in AI, wearable sensors, computer vision, Digital Human Modeling (DHM), and robotics, most studies remain laboratory based. Future investigations should emphasize long term field validation, improved system reliability, and integration of intelligent technologies into occupational health management (Apicella & Tarabella, 2025; Naranjo *et al.*, 2025) ^[5, 37].

10.1 Advanced Artificial Intelligence Modeling and Technical Refinement

Future AI research should develop advanced deep learning models such as CNN-LSTM and GCN-LSTM to better capture dynamic agricultural movements and repetitive tasks. Improvements in 3D pose estimation, multi-camera systems, and comprehensive agricultural posture datasets will enhance assessment accuracy under field conditions. AI should also evolve into decision-support systems capable of recommending personalized ergonomic interventions before injuries occur (Kapse *et al.*, 2024; Yang *et al.*, 2024; Massiris-Fernández *et al.*, 2020) ^[30, 34, 55].

10.2 Human-Centered and Inclusive Design

Future ergonomic technologies should consider worker diversity, including age, gender, anthropometry, and physical capability, to improve assessment accuracy and inclusiveness. Research should also address worker acceptance, privacy concerns, and cultural factors influencing technology adoption. Affordable AI systems, lightweight wearable devices, and user-friendly VR technologies will promote wider adoption, especially among small-scale farmers (Apicella & Tarabella, 2025; Hilmi *et al.*, 2024; Slob *et al.*, 2023) ^[5, 27, 51].

10.3 Systems Integration and Robotics

Future studies should integrate wearable sensors with farm management systems, Decision Support Systems (DSS), and Enterprise Resource Planning (ERP) platforms for comprehensive worker and farm monitoring. Human-Robot Collaboration (HRC) should prioritize worker safety and ergonomic support, while Digital Twin technology should enable realistic simulation of agricultural operations. Economic analyses, including cost-benefit and return-on-investment (ROI) studies, are also needed to demonstrate the practical value of digital ergonomic technologies (Adamides & Edan, 2023; Slob *et al.*, 2023; Peladarinos *et al.*, 2023; Naranjo *et al.*, 2025) ^[1, 37, 39, 51].

11. Conclusion

Agriculture remains one of the most ergonomically challenging occupations due to repetitive movements, awkward postures, heavy manual material handling, vibration, and adverse environmental conditions that increase the risk of work-related musculoskeletal disorders (WMSDs). This review demonstrates that digital ergonomics, integrated with Artificial Intelligence (AI), offers significant advancement over conventional observation based ergonomic assessment methods. Technologies such as wearable sensors, Internet of Things (IoT), computer vision, motion capture systems, Digital Human Modeling (DHM), Digital Twins, Virtual Reality (VR), and robotics enable continuous, objective, and real-time monitoring of workers' biomechanical, physiological, and environmental conditions. AI and machine learning further enhance ergonomic assessment through automated posture recognition, ergonomic risk classification, and predictive injury analysis, enabling early intervention before injuries occur. These technologies also support the design of ergonomically optimized tools, machinery, and workstations while promoting human-robot collaboration to reduce physical workload and improve operational efficiency. The review further highlights their successful application in harvesting, planting, weeding, pruning, and tractor operation, demonstrating their potential to improve worker safety, productivity, and overall occupational health. However, challenges such as limited field validation, high implementation costs, insufficient agriculture-specific datasets, sensor reliability under harsh environmental conditions, and worker acceptance continue to restrict widespread adoption. Future research should therefore focus on developing robust, affordable, and field-validated AI-driven ergonomic systems through multidisciplinary collaboration and user-centered design. Overall, the integration of digital technologies with AI represents a transformative step toward predictive, personalized, and preventive occupational health management in Agriculture 4.0. Continued advancements in these technologies will contribute to safer working environments, reduced incidence of WMSDs, improved farm productivity, and more sustainable agricultural work systems.

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