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Wearable Technologies in Agriculture 4.0: A Systematic Review of Applications for Worker Safety and Ergonomic Support

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Abstract

Purpose: The adoption of wearable technologies in agriculture is increasing in response to the growing need for solutions that enhance worker safety, monitor health conditions, and improve operational performance. This review investigates the current landscape of wearable devices applied in agricultural settings. The main research question explores how wearable technologies contribute to the prevention of occupational risks and the support of agricultural workers across different farming contexts. *Methods*: A systematic literature review was conducted according to the PRISMA protocol. A comprehensive search was performed in the Scopus database using a structured Boolean query to identify relevant peer-reviewed studies addressing wearable devices in agriculture with a focus on health, safety, and performance outcomes. The selection process included identification, screening, eligibility assessment, and full-text analysis. A total of 15 studies were included in the final review. *Results*: The reviewed studies report the use of various wearable technologies, including inertial measurement units, exoskeletons, smart glasses, and environmental sensors. Applications span viticulture, livestock farming, and general field operations. Wearable systems demonstrate high accuracy in posture detection, activity classification, and physiological monitoring. Positive impacts are observed in ergonomic support, fatigue reduction, and situational awareness. However, challenges remain regarding comfort, long-term usability, and validation under real-world conditions. *Conclusion*: Wearable devices show strong potential in advancing occupational health and operational efficiency in agriculture. Further research should focus on ergonomic optimization, long-term deployment, and integration with digital farm management systems to enable widespread and sustainable adoption.

Keywords: Wearable Devices, Agriculture 4.0, Worker Safety, Ergonomics, Occupational Health

Introduction

Contemporary agriculture is undergoing a profound technological transition, increasingly characterized by the adoption of digital, automated, and interconnected solutions (Karunathilake et al., 2023; Patrício and Rieder, 2018; Trivelli et al., 2019). This process, commonly referred to as "Agriculture 4.0", represents a systemic shift in the way agricultural production is planned, executed and monitored (Apicella and Tarabella, 2024a; Apicella and Tarabella, 2024b; Pedersen and Lind, 2017; Shaikh et al., 2022). At the core of this transformation lies the integration of advanced technologies, such as Internet-of-Things (IoT) sensors, mobile robotics, decision-support systems (DSS), wireless networks and cloud infrastructure that enable increasingly granular and data-driven control over agronomic and operational variables (Chlingaryan et al., 2018; Karunathilake et al., 2023; Khanna and Kaur, 2019; Klerkx et al., 2019; Singh and Singh, 2020). Within this framework, wearable technologies are rapidly emerging as strategic tools for extending digitalization to the human body, thereby making agricultural workers an integral component of the smart-farm ecosystem (Huuskonen and Oksanen, 2018). Wearable devices represent a class of technologies designed to be worn on the body and capable of real-time detection, transmission and analysis of a wide array of physiological, environmental, postural and biomechanical data (Iqbal et al., 2021; Kumari et al., 2017; Seneviratne et al., 2017). These solutions enable new forms of interaction between the operator, the working environment and digital infrastructures, thereby fostering a human-centered operational paradigm enhanced by technological support. In agriculture, this approach translates into the ability to monitor fatigue levels, heat stress, exposure to hazardous substances, improper postures and critical muscle dynamics, with the goal of preventing injuries, optimizing workload distribution and improving workers' overall well-being (Aiello et al., 2022; Etienne et al., 2024; Huuskonen and Oksanen, 2018). The relevance of wearable technologies in the agricultural domain is rooted in several distinctive characteristics of work within the primary sector. Unlike many industrial settings, agriculture is marked by high environmental variability, exposure to extreme climatic conditions, physically demanding tasks (such as pruning, lifting and load handling), and a labour organisation that is often fragmented, seasonal and poorly standardised (Aiello et al., 2022). In this context, wearable devices offer a technologically advanced yet flexible solution, capable of adapting to dynamic operational conditions and to users with different levels of technological literacy (Etienne et al., 2024). Furthermore, the integration of machine learning, deep learning and intelligent classifiers into wearable systems enables a shift from a reactive to a predictive logic, grounded in the anticipation of critical events and the implementation of proactive interventions (Anagnostis et al., 2021). From an application perspective, wearable devices employed in agriculture range from inertial measurement units (IMUs) for motion and posture analysis to exoskeletons designed to reduce biomechanical load, augmented-reality smart glasses, biometric bands for cardiac and thermal monitoring, and environmental sensors for detecting harmful gases (Aiello et al., 2022; Huuskonen and Oksanen, 2018). Some of these devices operate in synergy with embedded systems, cloud platforms and remote-supervision dashboards, ensuring real-time traceability and enabling prompt supervisory intervention. Others are designed to deliver immediate feedback to the operator through auditory alarms, vibrations or visual signals, thereby supporting autonomous decision-making and enhancing situational awareness (Huuskonen and Oksanen, 2018). Although scientific interest in agricultural wearables is increasing, literature remains fragmented, with studies differing considerably in their objectives, application domains, target populations and technological solutions. As a result, there is a growing need for systematic, comparative analyses capable of critically mapping the current state-of-the-art, identifying recurring design and functional patterns, and assessing the actual impact of these solutions on the prevention of biomechanical, environmental and health-related risks. In light of these considerations, the present study provides a systematic review of peer-reviewed scientific literature focused on the use of wearable technologies in agricultural and agro-industrial contexts. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009) and is based on a structured search strategy designed to identify studies situated at the intersection of wearable devices, worker centrality and the promotion of health, safety and physical performance in agriculture. The review pursues a dual objective. First, it seeks to map currently available technologies by classifying them according to technical and functional criteria, including device type, measured parameters, application domain, interaction modality and technological infrastructure. Second, it aims to assess the actual impact of these solutions on agricultural work, with respect to injury prevention, reduction of physical workload, improvement of environmental conditions and user acceptance.

Methodology

This study adopts a structured literature-review methodology that follows the PRISMA guidelines (Moher et al., 2009), thereby ensuring rigour, transparency and reproducibility throughout source selection and analysis. Publications were retrieved via an advanced Boolean query in the Elsevier Scopus database, widely regarded as one of the most comprehensive multidisciplinary indexing services (Chadegani et al., 2013; Singh et al., 2021; Zhu and Liu, 2020). The search was executed in April 2025 with all stages documented according to PRISMA (Moher et al., 2009). To identify relevant contributions on wearable technologies for monitoring and protecting agricultural workers, we developed a structured Boolean search strategy aimed at locating studies at the intersection of wearable technology, agricultural application, worker centrality and health, safety or performance outcomes.
The final search string was:

(“*wearable device*” OR “*wearable technolog**” OR “*smart wearable*” OR “*body sensor network*” OR “*wearable sensor*”) AND (“*agriculture*” OR “*farming*” OR “*agricultural field*” OR “*precision agriculture*” OR “*smart farming*”) AND (“*worker*” OR “*operator*” OR “*labor*” OR “*labour*” OR “*employee*” OR “*farmworker*” OR “*fieldworker*”) AND (“*health*” OR “*safety*” OR “*fatigue*” OR “*ergonomic*” OR “*stress*” OR “*monitoring*” OR “*performance*” OR “*occupational risk*”).

This search string was constructed to include four conceptual domains:

1. Wearable Technology: the first semantic block comprises terms describing wearable devices, ranging from general descriptors (e.g., “wearable device”) to more specific technical expressions (e.g., “body sensor network”, “smart wearable”). The truncation operator (*) captures lexical variants (e.g., “technology”, “technologies”).
2. Agricultural Context: this block refers to the application domain, including terms related to both traditional agriculture and more advanced forms such as “precision agriculture” or “smart farming”.
3. Worker Representation: here we include synonyms and orthographic variants denoting the human operator in agricultural settings, thereby ensuring broad terminological

coverage (e.g., “labor” vs. “labour”, “farmworker”, “employee”) and emphasizing the centrality of the human factor.

4. Health, Safety, and Performance Indicators: the final semantic block focuses on outcomes related to physical well-being, occupational risk, fatigue, stress, and physiological or environmental monitoring. The selected terms allow for the inclusion of research addressing both preventive strategies and performance evaluation.

The search was not restricted by year of publication in order to include both emerging contributions and well-established studies. Only peer-reviewed journal articles, conference proceedings, and book chapters published in English and with full-text availability were considered eligible. Theses, patents, technical reports, industrial documents, and, more generally, all forms of grey literature were excluded. The selection process was carried out in two successive phases. During identification, 53 records were retrieved using the predefined search string. After applying formal eligibility criteria, 41 articles progressed to the screening phase. Titles and abstracts of these 41 studies were examined for consistency with the review objectives, leading to the exclusion of 15 records for thematic irrelevance. In the eligibility phase, the remaining 26 articles underwent full-text assessment, which resulted in the exclusion of an additional 11 studies that did not align with the specific aims. Consequently, 15 articles met all methodological and content criteria and were included in the final systematic review.

The entire workflow was documented with a PRISMA flow diagram (Fig. 1), transparently illustrating the stages of identification, screening, eligibility assessment and inclusion.

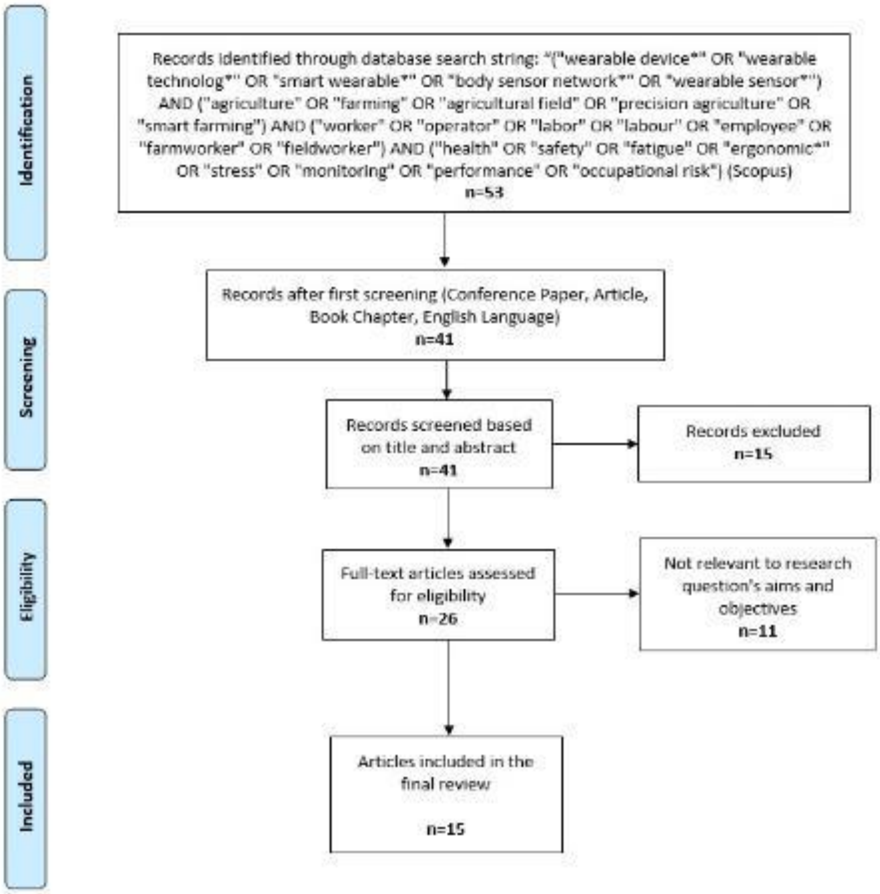

Figure 1. PRISMA Flow Diagram of the Study Selection Process. Source: Author's own elaboration

Results

This section reports the key findings of the systematic review, focusing on wearable devices for risk detection, injury prevention and operator support within agricultural work environments. As a first step, Table 1 provides a comparative overview of the wearable systems described in the included studies. For each device, the table lists the device class and anatomical placement, monitored parameters, sensing technologies, agricultural domain and functional outputs reported by the authors. The objective of this synthesis is to offer a snapshot of both commercial and prototype solutions, highlighting their technological heterogeneity, the diversity of operational objectives and their distribution across usage contexts. The table reveals multiple technical approaches ranging from miniaturised sensors for physiological and biomechanical monitoring, through exoskeletons for muscular assistance, to wearable interfaces that enhance communication and interaction. The application spectrum is equally diverse, covering viticulture, floriculture, precision livestock farming, smart-farming operations, agricultural logistics and injury-prevention tasks. Functional outputs range from automatic activity classification and threshold-based alerting to ergonomic assistance and remote expert support.

Table 1
Wearable Device Technologies, Applications, and Functional Outputs. Source: Author's own elaboration.

Device Type	Measured Parameter	Technologies Employed	Application Domain	Functional Output	Authors
Inertial band for wrist	Three-dimensional movements (quaternions)	IMU, LoRa, HTM, SDR	Smart farming – Predictive safety	Prediction of falls and activities with health alerts in smart farming	Adhitya et al., 2023
Aerogel sensor for face (mask)	Exhaled air humidity	AuNPs, PNIPAm	Health – Intelligent machine respiration monitoring	Continuous breath detection and voice recognition in smart masks	Ali et al., 2018
IMU sensors for chest, spine, and wrists	Acceleration, angular velocity, magnetic field	IMU, LSTM	Agriculture – Human–robot collaboration	Automatic recognition of six motor activities in agricultural settings	Anagnostis et al., 2021
Sensor patches – chest, forearm	Trunk inclination, muscle strain	Accelerometer, ECG, IMU, Sensors	Viticulture – Manual pruning	Posture detection and automated cut counting	Arrais et al., 2023
Arm bands	Temperature, humidity, noise, light, heart rate	Environmental sensors, alert-enabled band, cloud integration	Agriculture – Field activities	Environmental and physiological monitoring with multi-channel alert system	Cannady et al., 2025
Smart glasses	Visual stimuli (AR)	AR display, Inertial sensors	Animal husbandry – Precision livestock farming	Data access, subject identification, remote assistance and communication	Caria et al., 2019

Wrist/arm band	Distance between operators (COVID-19 contact tracing)	Bluetooth, GPS, NFC, cloud	Viticulture – Manual pruning	Auditory alert, contact tracing, supervisor notification	Catania et al., 2022
Elastic suit	Lumbar torque, EMG	Active band, wireless EMG, dynamometer	Agriculture – Simulated lifting	Lumbar support for strain reduction and MSD prevention	Cha et al., 2021
Lumbar support exoskeleton	— (no direct measurement)	IMU, EMG	Agriculture – Manual material handling	Reduction of lumbar load and improvement of physical ergonomics	Chittar and Barve, 2022
Sensors for hand, wrist, and forearm	Upper limb joint angles	ESP32, IMU, Bluetooth BLE, LCD, Kalman filter	Viticulture – Pruning simulation	Postural risk classification and real-time ergonomic feedback	Cividino et al., 2024
Printable sensor	Ammonia concentration in the air	SWCNT, Nafion, PET-based printing, Arduino	Agriculture – Environmental exposure	Resistive ammonia detection with rapid response	Hall et al., 2024
Body-worn RFID module	Operator position and proximity	RFID, WSAN, GPS/GNSS	Agriculture – Remote operation of mobile machinery	Safety monitoring in critical zones with automated actions and tracking	Pirozzi et al., 2020
Sensorized jacket for the chest	Height, trunk inclination, acceleration, magnetic field	SHIMMER3, MLP	Logistics – Lifting and handling	Lifting recognition and biomechanical risk reporting	Pistolesi and Lazzerini, 2020
Waistband	Acceleration, angular velocity	SHIMMER3, Bluetooth, ML (kNN, SVM, ANN)	Agriculture – Simulated activities	Movement monitoring for activity and fall detection	Son et al., 2022
Exoskeletons for back, shoulders, and legs	— (no direct measurement)	— (no technology tested)	Floriculture and nursery farming	Perceptions of exoskeletons: fatigue reduction, limitations related to comfort and mobility	Villanueva-Gómez et al., 2023

Building on the comparative overview, the results are unpacked along eight analytical dimensions that integrate technical and contextual evidence and frame future trajectories for agricultural wearables:

- Type of study: nature of the publication (experimental, conceptual, or simulation-based), level of technological maturity, and operational setting;
- Study population and operational context: number and profile of participants involved, type of activities performed, real-world or simulated environments;
- Types and characteristics of the devices analyzed: design and structure, body part involved, portability, and usage modalities;
- Integrated technologies and recorded metrics: types of sensors (inertial, physiological, environmental), monitored parameters and data processing methods;
- Software and hardware employed: microcontrollers, embedded platforms, development environments, communication modules, and computational architectures;

- Type of cultivation or agricultural task analyzed: segmentation by agricultural sector (e.g., viticulture, livestock farming, horticulture), specific activities (e.g., pruning, lifting, machinery operation);
- Validation and main findings: testing methods, accuracy or efficacy metrics, comparison between models or prototype versions;
- Impacts on the workers: ergonomic implications, perceived acceptability, usability challenges and prospects for operational transferability.

This multidimensional framework supports a critical reading of the current evidence and highlights research gaps and design priorities for the effective and sustainable adoption of wearable technologies in agriculture.

Type of Study

Several empirical studies develop and validate wearable systems aimed at preventing physical and biomechanical risks among agricultural workers. Among these, Cha et al. (2021) evaluate an assistive suit that reduces lumbar muscular load during lifting tasks, while Cividino et al. (2024) validate a sensor that quantifies wrist- and forearm-posture during grapevine pruning. A similar approach is adopted by Pistolesi and Lazzerini (2020), who integrate barometric and inertial sensors to detect hazardous lifting, and by Arrais et al. (2023), who monitor trunk inclination and cutting frequency during pruning activities. From a comparative perspective, Chittar and Barve (2022) benchmark lumbar exoskeletons, focusing on material selection and ergonomic impact. In the field of human-activity recognition (HAR), Anagnostis et al. (2021) employ IMU sensors and LSTM networks to classify six sub-tasks during crate transportation, while Son et al. (2022) use SHIMMER3 devices with ANN, SVM and k-NN models to distinguish falls from routine activities. Complementarily, Pistolesi and Lazzerini (2020) differentiate safe and hazardous lifting using AI techniques, and Adhitya et al. (2023) apply HTM classifiers to simulated data to detect dangerous movements in agricultural scenarios. Regarding the monitoring of environmental and physiological factors, Hall et al. (2024) develop an ammonia sensor based on SWCNTs, while Ali et al. (2018) design a conductive aerogel sensitive to humidity and respiration that is suitable for integration into wearable masks. Cannady et al. (2025) adopt a qualitative design to explore workers' perceptions of commercial heat-stress monitors. Other studies focus on smart applications in real-world production contexts. Catania et al. (2022) trial a wearable system for COVID-19 prevention in agricultural settings; Caria et al. (2019) evaluate an AR device for precision livestock farming, highlighting its versatility for remote assistance and data visualisation; and Pirozzi et al. (2020) propose a WSAN integrated with RFID sensors to enhance safety around remotely operated machinery. Finally, Villanueva-Gómez et al. (2023) investigate migrant seasonal workers' perceptions of exoskeletons in nursery work, revealing conditional openness influenced by comfort, heat and task compatibility.

Study Population and Operational Context

Experimental studies conducted under real operational conditions highlight a growing interest in applying wearable devices in agricultural and livestock contexts. Specifically, Catania et al. (2022) test their system in a Sicilian vineyard during winter pruning, involving three pruners working in close proximity—an arrangement suited to monitoring interpersonal interactions. Similarly, Arrais et al. (2023) validate a posture-monitoring system in vineyards of the Douro region (Portugal), employing two operators across three pruning sessions and synchronising sensor data with video footage. Cividino et al. (2024) replicate pruning in a laboratory, using a vine model and engaging four operators in repeated sequences to standardise conditions. In the livestock sector, Caria et al. (2019) conduct field tests on a Sardinian sheep farm, analysing routine tasks—animal identification, feeding and milking—to evaluate an AR device in everyday scenarios. Cannady et al. (2025) engage six workers in Nebraska who perform maintenance, animal care and machinery operation, exploring usability and acceptability of heat-stress monitors under challenging climatic conditions. From a biomechanical perspective, Cha et al. (2021) involve fifteen workers in controlled lifting tasks (5–20 kg) with squat and stoop postures, selected for their ability to lift ≥ 40 % of body weight. Son et al. (2022) recruit 40 participants to simulate agricultural activities and falls in a controlled arena, whereas Pistolesi and Lazzerini (2020) test their system both in a laboratory (30 subjects) and in an industrial logistics site (nine workers), capturing a broad range of real movements with variable loads. Anagnostis et al. (2021) operate in open fields, involving 20 subjects who manually transport crates to agricultural robots on a central-Greek farm. With a qualitative approach, Villanueva-Gómez et al. (2023) examine the perceptions of nine migrant seasonal workers in a Canadian nursery, observing tasks such as plant propagation and handling under heat stress and repetitive loads. Other investigations remain at the simulation or design stage. Hall et al. (2024), Pirozzi et al. (2020), Chittar and Barve (2022), Adhitya et al. (2023) and Ali et al. (2018) do not yet involve human subjects; instead, they report laboratory or simulated-data validations of environmental sensors, exoskeleton prototypes, predictive architectures and novel materials, outlining future applications in physiological and environmental monitoring for agriculture.

Types and Characteristics of the Devices Analyzed

The wearable devices analyzed across the various studies exhibit substantial technological heterogeneity, encompassing solutions ranging from environmental and biometric sensors to assistive exoskeletons and systems for posture and motion monitoring. In the domain of environmental and physiological monitoring, Catania et al. (2022) propose an electronic wristband for interpersonal distancing and contact tracing, while Cannady et al. (2025) evaluate MākuSafe for environmental variables and SlateSafety V2 for biometric parameters. Hall et al. (2024) develop a sensor on PET film using SWCNTs for ammonia detection, and Ali et al. (2018) design a hybrid gold-polymer aerogel sensitive to humidity, applicable in wearable masks for respiratory monitoring. In the field of assistive and exoskeletal devices, Cha et al. (2021) test an elastic suit with a lumbar actuator designed to support lifting motions, while Chittar and Barve (2022) offer a systemic analysis of lumbar exoskeletons (rigid, soft, and hybrid), with a focus on transmission mechanisms and materials. Although they do not test real devices, Villanueva-Gómez et al. (2023) assess the perceived acceptability of three types of exoskeletons (back, shoulder, and chairless chair) among seasonal workers. A third category comprises systems for monitoring movement, posture, and biomechanical risk. Arrais et al. (2023) employ the VitalSticker and SnapKi, respectively for physiological signal acquisition and muscular dynamics during pruning. Cividino et al. (2024) develop a system based on the ESP32 platform with triaxial IMUs, applied to the hand, wrist, and forearm for kinematic analysis. Anagnostis et al. (2021) use Blue Trident IMU sensors on five body segments to train LSTM networks for activity recognition. Son et al. (2022) utilize a single SHIMMER3 device mounted at the waist to classify falls and agricultural movements, whereas Pistolesi and Lazzerini (2020) integrate two Shimmer3 sensors—equipped with accelerometers, magnetometers, and barometers—into a high-visibility work jacket designed to detect incorrect lifting behaviors. Finally, some solutions stand out for their communicative and management functions. Caria et al. (2019) test the GlassUp F4 smart glasses, originally designed for industrial use, featuring a monocular display, camera, and multiple sensors, controlled via joypad or button, and highlight their potential application for remote assistance in precision livestock farming. Adhitya et al. (2023), in a simulated environment, propose a theoretical system based on wrist-worn inertial sensors and classification through quaternion-based features and an HTM network, aimed at predictive safety in agricultural settings.

Integrated Technologies and Recorded Metrics

The wearable systems analysed exhibit a stratified diversity of sensing, communication and inference technologies, each tailored to specific agricultural, livestock or agro-industrial applications. At the connectivity layer, short- and long-range wireless solutions intertwine: Catania et al. (2022) combine Bluetooth Low Energy 5.0, GPRS/GPS and NFC to log spatio-temporal interactions among vineyard workers, maintaining coverage even in rural areas with limited connectivity, whereas Pirozzi et al. (2020) deploy WSN/WSAN meshes coupled with RFID tags to detect hazardous situations around remotely operated machinery and to trigger automated responses. Caria et al. (2019) extend the same infrastructure to wearable displays, using smart-glasses that handle QR-code reading, bidirectional data streaming and low-latency video during livestock tasks. Physiological and environmental monitoring form a second layer. Cannady et al. (2025) encode OSHA–ACGIH thresholds for heat, humidity and noise, issuing vibrotactile and digital alerts when limits are exceeded. Hall et al. (2024) register resistive shifts proportional to NH_3 concentration (linear up to 1 100 ppb, $R^2 = 0{\cdot}99$), while Ali et al. (2018) translate humidity-driven conductivity changes in gold–polymer aerogels into respiratory indicators, even parsing acoustic traces such as whistling. A third layer addresses posture and biomechanics. Arrais et al. (2023) fuse IMU data sampled at 10–50 Hz with force sensors to estimate trunk inclination and pruning cadence; Cividino et al. (2024) construct a kinematic arm model, comparing joint angles against ergonomic thresholds; Cha et al. (2021) integrate dynamometry with 16-channel EMG to quantify lumbar muscle unloading provided by an assistive suit. Machine-learning pipelines then convert sensor streams into actionable labels. Pistolesi and Lazzerini (2020) derive 28 inertial–magnetic features, reduce them to six salient variables and classify lifting safety; Anagnostis et al. (2021) train an LSTM on overlapping two-second windows to recognise six crate-handling sub-activities; Son et al. (2022) extract 54 statistical-spatial descriptors from a waist-mounted SHIMMER3 and compare k-NN, SVM and ANN models via AUC, F1 and MCC; Adhitya et al. (2023) simulate quaternion-based inputs processed by a hierarchical temporal memory architecture, evaluating MAE, MSE and RMSE. Finally, Villanueva-Gómez et al. (2023) perform NVivo-based thematic analysis of interview transcripts, classifying workers' perceptions, reported symptoms and evaluations of exoskeleton archetypes, thereby foregrounding the human factors that mediate technological adoption.

Software and Hardware Employed

The wearable and sensor systems presented across the studies employ heterogeneous hardware and software architectures, tailored to specific operational requirements. Some devices stand out for their hardware complexity and integration of multiple modules: Catania et al. (2022) equip their device with an ARM CPU, multi-constellation GPS module, GPRS, NFC, and a lithium battery, providing data updates every 5 seconds accessible via a cloud platform. Caria et al. (2019) utilize GlassUp F4 smart glasses running a Linux-based system, managed through a dashboard and external joypad, with usability tests conducted under 4G mobile connectivity. Similarly, Hall et al. (2024) employ an Arduino Uno for resistive monitoring and an XYZ system for controlled-environment sensor fabrication. Other devices leverage embedded systems and microcontrollers. Arrais et al. (2023) develop algorithms in Matlab®, later deployed on an Android app and connected via Bluetooth to VitalSticker and SnapKi sensors, with webserver support for remote consultation. Cividino et al. (2024) use Arduino for firmware management, BLE 4.2 for transmission, and Python for data processing, incorporating a Kalman filter. Pistolesi and Lazzerini (2020) also design a multilayer perceptron (MLP) neural network in MATLAB using the Levenberg–Marquardt algorithm, optimized for both accuracy and battery efficiency. From a computational and machine learning perspective, Anagnostis et al. (2021) utilize Capture.U for data acquisition, followed by normalization and LSTM training within a Python/TensorFlow environment. Son et al. (2022) implement kNN, SVM, and ANN models using scikit-learn and Keras, with repeated validation procedures. Adhitya et al. (2023) also operate in Python, simulating a system compatible with LoRa networks for telemedicine data transmission, while Chittar and Barve (2022) describe the integration of EMG/IMU sensors and actuators within real-time adaptive control systems. Regarding cloud infrastructure and remote management, Cannady et al. (2025) describe the use of cloud-based platforms for managing biometric and environmental data. Pirozzi et al. (2020) likewise emphasize secure wireless transmission and protocol compatibility, although implementation details are not provided. In the qualitative and non-instrumental domain, Villanueva-Gómez et al. (2023) employ NVivo v11 for coding Spanish-language interviews, using triangulation among coders. Although Ali et al. (2018) do not implement a complete platform, they test their sensor in a simple circuit and characterize the material using advanced techniques (XRD, SEM, TEM, XPS), indicating future potential for integration into portable wearable devices.

Type of Cultivation or Agricultural Task Analyzed

Several experimental studies target crop-specific operations, with manual viticulture taking centre stage. Catania et al. (2022) conduct field trials in a Sicilian vineyard trained to Guyot, monitoring close-range winter pruning. Arrais et al. (2023) test their device during pruning in Portugal's Douro region and foresee extensions to harvesting and thinning. Working in a laboratory vine model, Cividino et al. (2024) simulate spur-pruned cordon management and propose further use in harvesting, tying and olive cultivation. The livestock sector is represented by Caria et al. (2019), who evaluate smart-glasses during routine dairy-sheep tasks—milking, feeding and inspection—in a noisy barn, emphasising QR-code access to husbandry data. A second group of studies addresses generic, load-intensive activities. Cha et al. (2021) analyse upright and squatting lifts typical of greenhouse logistics, while Son et al. (2022), Adhitya et al. (2023) and Cannady et al. (2025) replicate harvesting, irrigation, transportation and bending in high-temperature settings. Pistolesi and Lazzerini (2020) concentrate on manual load handling, a key risk factor across agricultural and logistics domains. Other contributions explore technology-mediated or environment-critical scenarios. Anagnostis et al. (2021) study crate transport to UGV robots during fruit harvesting; Pirozzi et al. (2020) outline a safety network for remotely operated agricultural, forestry or construction machinery; Chittar and Barve (2022) focus on confined spaces where exoskeletons outperform heavy equipment. Specialised environmental monitoring appears in Hall et al. (2024), who target chronic ammonia exposure in livestock houses, greenhouses and composting sites, and in Villanueva-Gómez et al. (2023), who investigate ornamental nurseries with heterogeneous, load-variable tasks up to 50 kg. Finally, Ali et al. (2018) propose their humidity-responsive aerogel for fatigue and breath-moisture monitoring in high-risk respiratory settings, although field validation remains pending.

Validation and Main Findings

The evidence base consistently indicates high technical accuracy and reliability across the tested wearables. Arrais et al. (2023) report an RMSE of 1.36 ° for trunk inclination and a mean error of 2·4 cuts in counting tasks, with accuracies ranging from 72% to 98%. Cividino et al. (2024) achieve statistically significant repeatability ($p < 0.01$) and observe that 40% of simulated gestures exceed ergonomic thresholds. Pistolesi and Lazzerini (2020) attain 95.6 % accuracy in lift classification, with 100% recall and precision for unsafe lifts; similarly, Son et al. (2022) reach AUC = 1.00 and accuracy = 99.84 % with ANN, and AUC = 0.988 under multiclass SVM. In predictive tasks, Anagnostis et al. (2021) record 85.6 % overall accuracy, highest for unloaded walking and lowest for bending, whereas Adhitya et al. (2023) obtain 88% on validated data but only 54% on simulated sets, with low recall in specific classes. Ali et al. (2018) validate their humidity sensor by clearly separating healthy from ill subjects and detecting musical respiratory sounds, thus confirming high sensitivity. Biomechanical findings corroborate assistive benefits: Cha et al. (2021) report up to 31% reduction in muscle activity during stoop lifts, albeit with a 17% rise in lumbar torque, while Villanueva-Gómez et al. (2023) show that BX, CX and SX exoskeletons are deemed useful for lifting, stationary or overhead tasks, though weight, heat and bulk remain concerns. Usability outcomes are likewise positive. Catania et al. (2022) confirm robust anti-contagion wristband performance and secure cloud back-up; Caria et al. (2019) note QR-code scan times of 7–11 seconds, seven-hour autonomy, stable audio-video streams and readability up to 3 meters in low light. Cannady et al. (2025) report general acceptance of heat-stress monitors but flag comfort issues and gaps in emergency protocols. Several works remain at a design or specification phase. Pirozzi et al. (2020) outline functional requirements aligned with ISO standards without presenting field data, and Chittar and Barve (2022) provide a theoretical material screening that identifies Al 7075 and carbon fibre as the best trade-off between weight, cost and performance.

Impact on the Workers

The analyzed wearable devices demonstrate significant potential benefits for the health, safety, and ergonomics of agricultural workers, although constraints linked to comfort, thermal burden and adaptability persist. In the domain of health prevention and monitoring, Catania et al. (2022) highlights the effectiveness of their system in tracking only high-risk contacts, ensuring both operational continuity and privacy. Similarly, Cannady et al. (2025) show that heat stress monitoring devices can raise risk awareness and promote timely responses, although issues related to fixation and comfort are reported. Hall et al. (2024) and Ali et al. (2018) underscore the utility of gas and respiratory sensors for preventing respiratory illnesses, even though these devices have not yet been tested under real operating conditions. Regarding ergonomics and biomechanical load reduction, Arrais et al. (2023), Cha et al. (2021), Cividino et al. (2024), and Pistolesi and Lazzerini (2020) converge on the relevance of wearable systems for posture monitoring, lumbar support, and identification of hazardous movements. The assistive devices analyzed, including elastic suits, SnapKi, and IMU sensors, enable personalized corrective interventions, improving posture and reducing fatigue. However, Cha et al. (2021) and Villanueva-Gómez et al. (2023) note that in dynamic situations, compensatory muscles may be activated, or that devices can be bulky, hot, and insufficiently flexible. Technological integration into production processes emerges as a key aspect. Caria et al. (2019) demonstrate how smart glasses allow hands-free operation and remote assistance, improving efficiency in livestock farming. Pirozzi et al. (2020) suggest that combining wearable systems with remotely operated machinery may mitigate traditional risks, while introducing new challenges related to interoperability and environmental safety. Adhitya et al. (2023) and Son et al. (2022) emphasize the predictive value of AI-based systems for future safety applications, particularly in smart farming and rural telemedicine. From a perceptual and social standpoint, Villanueva-Gómez et al. (2023) report a general openness to exoskeleton use, perceived as protective and physically relieving, although concerns persist regarding comfort and adaptability. Similarly, Cannady et al. (2025) find that while participants did not raise privacy concerns, continuous tracking increased their self-awareness regarding work behaviors.

Discussion

The analysis of the selected studies reveals a complex and rapidly evolving landscape in the use of wearable technologies for monitoring, prevention, and assistance in agricultural settings. The devices vary in terms of functional purpose, ranging from health prevention and biomechanical support to environmental monitoring, but converge on a shared goal: mitigating risks to workers through intelligent, portable solutions adaptable to dynamic operational contexts. A first notable finding concerns the body areas most frequently targeted by these technologies. The lumbar region and lower back are the primary focus of monitoring efforts, as they are particularly prone to overload during lifting and manual material handling tasks (Cha et al., 2021; Pistolesi and Lazzerini, 2020; Chittar and Barve, 2022). Upper limbs, especially the wrist, hand, and forearm, are also receiving increased attention (Cividino et al., 2024; Arrais et al., 2023), while respiratory (Hall et al., 2024; Ali et al., 2018) and thermal sensors (Cannady et al., 2025) reflect a growing interest in the surveillance of less visible yet strategically relevant physiological parameters. From a technological standpoint, the integration of Inertial Measurement Units (IMUs) emerges as the most widespread solution for motion and posture analysis (Anagnostis et al., 2021; Son et al., 2022). These are complemented by EMG sensors for muscular activity (Cha et al., 2021), GPS and Bluetooth modules for localization and tracking (Catania et al., 2022), and emerging technologies such as smart glasses (Caria et al., 2019) and nanostructured materials for environmental sensing (Hall et al., 2024). The adoption of artificial intelligence models, particularly neural networks, LSTM, and HTM classifiers, enables real-time, context-adaptive predictive analyses (Adhitya et al., 2023; Son et al., 2022). Perceived impacts among workers are generally positive, particularly regarding physical load reduction, increased risk awareness, and enhanced operational autonomy. Qualitative studies (Villanueva-Gómez et al., 2023; Cannady et al., 2025) indicate an overall openness to the introduction of exoskeletons and sensors, although concerns persist regarding comfort, bulkiness, and adaptability. A recurring limitation in literature analyzed is the heterogeneity of experimental protocols. Only a subset of studies combines both laboratory and field testing (Cividino et al., 2024; Arrais et al., 2023), while others rely exclusively on simulations (Adhitya et al., 2023; Ali et al., 2018), limiting the external validity and operational generalizability of the results.

Conclusions

Wearable devices are emerging as high-potential tools for promoting health, safety, and operational efficiency in the agricultural sector. The evidence reviewed demonstrates how diverse technologies, including IMUs, exoskeletons, environmental sensors, and augmented reality, can contribute to reducing biomechanical risks, monitoring critical physiological parameters, and supporting workers' decision-making autonomy. The ability of these systems to provide real-time data, combined with machine learning algorithms, enables the anticipation of critical events, the personalization of preventive strategies, and the segmentation of risk profiles. The benefits also extend to training and remote support, with concrete applications in livestock farming and precision viticulture (Caria et al., 2019; Cividino et al., 2024). From an ergonomic perspective, most devices are compatible with existing agricultural equipment, offering low-impact and unobtrusive solutions (Pistolesi and Lazzerini, 2020). Despite these promising outcomes, the present analysis has some methodological limitations. First, the reviewed literature is marked by considerable heterogeneity in experimental designs, with significant variation in test duration, sample size, and validation environments. Moreover, only a limited number of studies adopt longitudinal follow-ups capable of evaluating the medium- and long-term impact of these technologies. For agricultural managers and safety officers, the findings suggest the opportunity to progressively integrate wearable devices into operational practices, especially in high-risk contexts such as pruning, lifting, milking, and manual handling of loads, or in physiologically demanding environments involving thermal or respiratory exposure. The data collected can support more informed decisions regarding task allocation, targeted training, and predictive maintenance, contributing to continuous performance improvement and operator well-being. From a public policy perspective, incorporating wearable technologies into occupational health and safety strategies could represent an innovative direction for revising agricultural labor regulations. Investment in rural digital infrastructure is also desirable to ensure the connectivity required for real-time device functionality. Future research should prioritize three main directions: 1) Long-term validation of wearable systems under real operational conditions, through multicenter longitudinal studies with more robust experimental designs; 2) Ergonomic and adaptive optimization to enhance usability in dynamic agricultural scenarios, accounting for anthropometric, climatic, and cultural variables; 3) Integrated cost–benefit evaluation, using economic models that assess return on investment (ROI) in terms of injury reduction, productivity gains, and workforce retention. An additional avenue for development concerns the interoperability between wearable devices and farm digital systems (e.g., ERP, DSS), with the aim of integrating biometric data with performance, environmental, and management indicators thus advancing toward truly intelligent, human-centered agriculture.

Theoretical and Contextual Contribution

This study contributes to the evolving discourse on Agriculture 4.0 by focusing on the role of wearable technologies in enhancing occupational health, safety, and ergonomic support for agricultural workers. Theoretically, it expands upon models of technology adoption in agriculture by introducing a human-centered perspective that positions the worker not as a passive recipient of technological change but as an active and digitally integrated agent within smart farming ecosystems. This orientation complements and challenges prevailing narratives that emphasize mechanization and automation while neglecting the embodied experience of agricultural labor. By systematically synthesizing evidence across diverse technological categories—ranging from inertial and physiological sensors to exoskeletons and augmented reality—the review advances a conceptual framework that foregrounds the body as a site of both vulnerability and intervention within digital agriculture. Moreover, the study contributes to the literature on occupational health and human–technology interaction by showing how wearable systems mediate the relationship between the operator, the environment, and data infrastructures. Through this mediation, wearables enable not only real-time monitoring but also predictive risk assessment and adaptive feedback, thus supporting a shift from reactive to proactive safety cultures. The integration of AI techniques (e.g., LSTM, ANN, HTM) in wearable architectures further reinforces this transition, offering methodological insights into how intelligent sensing can be tailored to dynamic, high-variability agricultural contexts. Contextually, this review is situated within a sector characterized by structural precarity, environmental unpredictability, and physical strain—factors that have historically limited the applicability of rigid industrial safety models. Agriculture presents unique ergonomic and organizational challenges: seasonal labor, fragmented tasks, outdoor exposure, and heterogeneous user profiles. By encompassing empirical evidence from viticulture, livestock farming, horticulture, and logistics, the review highlights the situatedness of wearable applications and the need for flexible, context-sensitive design principles. It also underscores the socio-cultural dimensions of technological acceptance, particularly among migrant and seasonal workers, revealing tensions between innovation and usability, autonomy and surveillance. Ultimately, the study bridges technical and human-centered approaches to agricultural innovation, offering a comprehensive synthesis that informs both academic theorization and applied decision-making. It provides a structured basis for future research on the ergonomics, usability, and policy implications of wearable systems, and contributes to an inclusive vision of digital agriculture where worker safety and well-being are not by-products but core design criteria.

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